
What Fuels the Electric Vehicle Market?

An Investigation of Macroeconomic and Sustainable Drivers of the Electric Vehicle Market

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DECLARATION

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SUMMARY

This doctoral thesis provides an investigation of three important determinants of the electric vehicle market and their respective influences on the market. Employing a data driven approach to counteract the shortcomings of previous research that focused on electric vehicle adoption intention, this study circumvents the attitude-action gap and attempts to answer the questions whether environmental awareness, innovativeness and financial subsidies are decisive factors for the development of the electric vehicle market.

The first investigation is concerned with determining whether environmental awareness is a significant factor for the electric vehicle market. Employing a macroeconomic perspective and introducing a new measurement method of environmental awareness in form of Twitter keyword analysis to gauge the society's level of environmental awareness, this research rules out the significance of this altruistic factor. Further, support for this finding is provided by altering the measurement method of environmental awareness and using Google Trends instead.

Determining that the altruistic factor does not play a significant role for the development of the electric vehicle market, in the second study the variable of interest embodies rather self-centered properties. In particular, it is investigated whether innovativeness influences the electric vehicle market, using a surrogate variable that can represent the innovativeness level of a country's citizens, companies and government. In contrast to the first study, the results of different econometric approaches applied in this study imply a positive and significant influence stemming from a country's level of innovativeness.

Finally, it is analysed whether subsidies are able to bridge the gap and reduce the market barrier of higher prices of electric vehicles. Applying various statistical approaches, the results of the investigation do not only provide proof for a significant influence of subsidies but also provide evidence for differences in the influence depending on the specific vehicle type.

DEDICATION

To whom it may concern.

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What started as a mentor protégé relationship, developed into a great friendship. I would have never thought I would start a career in academia had it not been for Sam who sparked my interest in research during the process of my MSc. in Finance dissertation in 2019. When he asked me to become his PhD student I could not yet have imagined that two years later we would be sitting together on a boat in Greece trying to pass our Day Skipper license and desperately trying not to sink the boat. Sam has been a pillar for me during this thesis and I could not have wished for a better supervisor. He gave me the freedom to explore my own ideas but was always there if I needed advice, be it on topics regarding my research or my academic career. Sam once asked his own PhD supervisor Professor Lucey how he could repay him for all his support. Professor Lucey told him to carry on the favour when looking after his own doctoral student one day. I am convinced Sam has more than carried forward the favour and I will forever be grateful for his patience and support. While I have had the utmost luck having such a great supervisor, I feel even more fortunate to say that during my time as his PhD student we have also become very good friends. I look forward to my continued cooperation with him professionally as well as personally and can not wait to get started on the Coastal Skipper course with him and my brother Alex next year.

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INTRODUCTION

The purchase of a car is one of the most expensive investments in the lives of many people. While for some people a car is just a means of transportation, for others there is also an emotional aspect in the selection of a vehicle involved. A car is for example often considered to be a symbolic motive which individual's can use to express themselves (Dickerson and Gentry, 1983). Moreover, it is also often used as a status symbol. Considering the high price of a car and the emotional aspect that is involved in the selection process, the purchase of a car is often well thought through. While there were previously already a wide range of car brands, designs and models, the decision making process has become even more complex with the development of new alternative propulsion systems. Especially in recent years, with advancements in the technology alternative fuel vehicles became a more feasible alternative to the traditional market dominating diesel and petrol cars. One alternative propulsion system that strikes out as it witnessed significant market growth in the last years are electric vehicles (EV). This vehicle type appears to be a great opportunity to significantly reduce the CO_2 emissions in the transportation sector but also requires substantial behavioral changes by the customers (Rezvani et al., 2015). Due to its potential role in mitigating climate change on the one hand and the expected difference to and influence on the traditional ICC market on the other hand, investigating driving factors of the EV market is not only important for market practitioners and the environment but also for entire economies such as Germany. This is because Germany's economic

growth to a relatively large part depends on the development of this sector as it accounts for about 20% of the total industry turnover (Germany Trade and Invest, 2021). Based on the aforementioned reasons, the EV market has received growing attention over the last years. This thesis contributes to the stream of research investigating the driving factors of the EV market by looking at the influence of three distinct determinants.

1.1 Background and Motivation

Climate change is today's biggest threat to the planet (IPCC, 2014). Natural disasters, expected to continue to increase in frequency, are often assumed to be a direct result of climate change and not only cause severe economic damages but also claim lives (Coronese et al., 2019). As a consequence, the international community has agreed upon several treaties and pledged to engage in environmental protection measures. One of the most prominent treaties, established by the United Nations, which is ratified by 188 states and the EU, making it to one of the geographically most extensive treaties, is the Paris agreement (United Nations Climate Change, 2020b). The decisions which are being made at conferences taking place in relation to this agreement are historically a few of the most capital intensive (United Nations Climate Change, 2020a). Consequently, climate change is of economic interest not only due to the negative impacts of catastrophes but also due to the measures required to prevent a deterioration of the situation. This in turn also makes climate change an important topic from a financial perspective.

When looking closer at the Paris agreement, it can be seen that a main aspect of the treaty is to keep the increase in average temperature below 2C° compared to pre-industrial levels. This can only be achieved by drastically reducing the anthropogenic greenhouse gas emissions. As it is one of the main greenhouse gasses it is therefore unavoidable to reduce CO_2 emissions. To identify areas with the highest potential impact of a reduction of CO_2 emissions, it is of interest to look at the sectors with the highest emission rates. As depicted in Figure 1.1, in the European Union the transportation sector is the second largest contributor to CO_2 emissions, responsible for 1,226 million tonnes of greenhouse gases in 2016 and therefore accounts for almost 27% of the overall emissions in the EU. Diving further into it, the largest share of CO_2 emissions (44.3%) in the transportation sector are emitted by passenger cars (see Figure 1.2) (European Environment Agency, 2019).

In order to meet the climate goals set in the Paris agreement and to address the need for a global reduction of CO_2 emissions, a focus on the private transportation sector becomes evident. To achieve the recently set target in the European Green Deal of becoming a CO_2 neutral continent by 2050 (European Commission, 2019), innovative solutions in this sector are required.

What also makes the private transportation sector highly interesting from an economic and business perspective is that a promising alternative to normal internal combustion cars is already available on the market. Often discussed in academic literature as well as in politics electric vehicles (EVs) are seen as a potential solution to the high rate of emissions in this sector. Incorporating the ability to either significantly reduce (plug-in hybrid electric vehicle (PHEV)) or completely eliminate (battery electric vehicle (BEV)) the emission of GHG, these types of cars provide a potential solution to mitigate climate change. As the change from an ICC to an EVs is accompanied by significant behavioral changes and this vehicle type in general still faces severe market barriers, it is crucial to investigate the driving factors of this market (Rezvani et al., 2015). Only a transition to a more sustainable transportation mode can prevent irreversible damage to the environment. Since EVs are currently the most promising solution, this research is motivated by the desire to help accelerate the diffusion of this innovation.

Figure 1.1: CO_2 Emissions by Sector

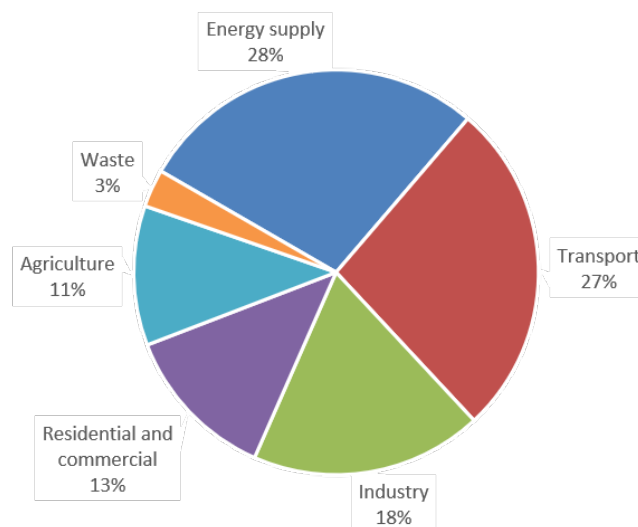
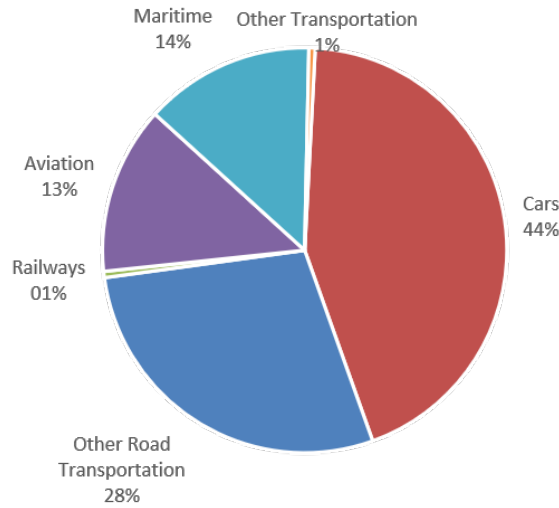


Figure 1.2: CO_2 Emissions by Transportation Mode

1.2 Contribution

In this thesis the main focus is laid on investigating the influence of three determinants of the EV market. While two of these determinants can be categorised as psychological determinants, one of them is of a more macroeconomic nature. In particular, the two psychological determinants are environmental awareness (EA) and innovativeness and the macroeconomic factor investigated is the influence of subsidies on the EV market. Thereby, the relationship and structure between the determinants can be seen as a type of dialectic. To be precise, EA, innovativeness and subsidies reflect a thesis, antithesis and synthesis respectively. The proposed thesis is that the underlying driver of the EV market is of altruistic nature and in particular the aim is to save the environment. The rationale behind this thesis is based on the property of EVs to be a more environmental friendly means of transportation. Hence, it is hypothesised that people purchase an EV to reduce their CO_2 -emissions and thus trying to save the environment. In contrast to the thesis the corresponding antithesis is that more self-centered values drive the development of this market as it still faces too severe barriers which make altruistic factors less relevant for the development of this market. Considering that EVs have only recently been introduced to the mainstream market and thus can be seen as an innovative product, an interesting self-centered factor to be investigated is innovativeness. Lastly, the investigation of the influence of subsidies on the EV

market is derived from a synthesis of thesis and antithesis. As already stated, it is assumed that market barriers hinder the adoption of EVs based on the altruistic factor EA. Hence by minimising these barriers, altruistic motives might also become a significant factor in this market. Consequently, in this dissertation a focus is laid on one market barrier in particular which is the higher purchasing prices of EVs compared to ICCs and the policy means, namely subsidies, through which governments are trying to minimise this price gap.

In general this research contributes to extant literature by taking on a macroeconomic perspective and using actual market data. As pointed out later in the literature review, research predominantly relied on using surveys and investigated adoption intention rather than actual adoption behavior. Hence, by employing actual market data the investigations performed in this thesis are able to circumvent the biases arising from the data collection method of surveys and not only validate the results of previous literature but also determine the marginal effects of these determinants. Further, taking on a macroeconomic perspective facilitates analyses of the effect from a different perspective which helps provide a more comprehensive understanding of previous findings. Another more general contribution is the European scope of the investigation. Previous research on the EV market is mostly centered around the US and China (Münzel et al., 2019). In the following more detailed contributions of each of the analyses of the three factors, which are presented in Chapters 6 - 8, are outlined.

1.2.1 Does Environmental Awareness Fuel the Electric Vehicle Market?

Countries worldwide are subsidising the purchase of EVs not only through monetary incentives but also through non-monetary incentives. While the effects of subsidies have been investigated by different scholars (e.g. Sierzechula et al., 2014; Mersky et al., 2016; Münzel et al., 2019), they do not offer a sustainable solution for the turnaround from internal combustion cars to EVs. Paradoxically, several countries decreased the amount of subsidies in recent years (Münzel et al., 2019); therefore calling on the individual to accelerate the development of the EV market.

As proposed by the theory of planned behavior (TPB) (Ajzen, 1991), which is frequently used as a framework to explain antecedents of purchasing behavior, an individual's attitude can be a major driver in the decision whether or not to

purchase an EV. One attitudinal dimension that comes to mind in relation to EVs is environmental awareness (EA). As mentioned earlier, EVs are by many politicians and scholars seen as an important step towards a more environment friendly transportation sector. In addition, many car manufacturers such as Mercedes Benz (Daimler, 2020) or Volkswagen (Volkswagen, 2020) are using sustainability and eco-friendliness as a key component of the brand they are building around their EV lines. As branding literature suggests, consumers are more likely to purchase from a brand that reflects their personal values and beliefs (Mitchell and Olson, 1981). This in turn indicates that whether or not an individual is concerned about climate change and sustainability, i.e. is environmentally aware, might play a role in his or her purchasing decisions regarding EVs. The underlying assumption would be that an increase in EA leads to more EV sales and hence more EV registrations.

Chapter 6 aims to investigate whether EA has a significant influence on the registrations of EVs to gain a better understanding of the sales drivers in this market. Thereby, a novel method to measure EA in form of a Twitter keyword analysis as well as a Google Trends analysis is applied. This method distinguishes itself from the predominantly used surveys in this field of research, as the results are not exposed to potential biases and exhibit macroeconomic characteristics rather than individual characteristics. Furthermore, it allows to address the gap in research that focuses on actual EV adoption. While most studies dealing with EA focus on one country, the properties of the considered method allow to investigate the effects for almost the entire EU and EFTA from 2010 to 2017. The results of the analysis indicate that EA does not significantly influence the EV market and thus contradicts with the majority of the findings of previous research. Since extant literature dealing with this research question focuses on adoption intention rather than actual adoption behavior, it can be concluded that this study provides further evidence for the prevalence of the attitude-action gap in this market. The results presented in Chapter 6 provide new interesting insights about the influence of the determinant, practitioners and politics can use to foster the development of the EV market. Moreover, it contributes to academic research by proposing new measurement methods to this field of research, that can especially be beneficial when focusing on a psychological determinant. From a theoretical perspective, this research also provides evidence for the importance of the perceived behavioral control dimension and the limited transferability of findings that are obtained by looking at adoption intention on actual adoption behavior.

1.2.2 Country Innovativeness: An Accelerator of the Electric Vehicle Market?

Do countries with a higher level of innovativeness adopt EVs faster than others? Although incorporating an electric propulsion system into a car is not a new idea and has already been implemented more than 150 years ago, only recently EVs have entered the mainstream market and are starting to become a real alternative to ICCs (Plötz et al., 2014). Based on the diffusion of innovation (DOI) theory developed by Rogers (1962), an individual that adopts new technologies faster than others is considered to be more innovative. This could imply that a country that exhibits a higher EV ownership is inherently more innovative than one with a lower ownership ratio and hence making this investigation redundant. It could however also be argued that the innovativeness of a country, which in turn means its citizens, companies and governments, can not solely be evaluated based on the adoption of a single new technology. Less innovative countries might for example exhibit other characteristics that mitigate the lack of innovativeness, thus making this variable less pertinent. Further, there is the possibility that there may be factors that inhibit even innovative customers to purchase an EV. Midgley and Dowling (1978) for example pointed out that there might be factors such as financial constraints that could restrain them from the purchase of a new technology. Considering that cars are a high cost product and EVs are substantially more expensive than comparable ICCs, it could be the case that innovative people neglect the purchase of an EV. Furthermore, the question arises whether EVs are an innovation at all as the only difference to traditional vehicles is the electric driven propulsion system. To answer the last question first, the majority of researchers (e.g. Schuitema et al., 2013; Rezvani et al., 2015; Kumar and Alok, 2020) recognise EVs as an innovation since it exhibits severe changes in the handling of a car. Especially adjustments regarding the refuelling behavior and planning of trips need to be made. It thus makes sense to also evaluate whether innovativeness is also a driving factor of this market.

Like EA, innovativeness can also be considered a psychological factor. Hence, it is not surprising that the influence of innovativeness was only analysed on individual's purchase intention of EVs. Consequently, similar biases as identified before could have influenced the results of previous investigations in this stream of research. Thus, by employing actual market data and using a more objective

measurement of innovativeness, this research can validate or refute the findings of the extant literature. Furthermore, there is a lack of research analysing the influence of the innovativeness level of companies or the government which are beside the citizens in a country also a potential large customer group of this vehicle type. Hence, by choosing an adequate surrogate that can represent the innovativeness level of all three groups, previous findings can substantially be extended by a broader spectrum of customers. Employing a macroeconomic view and considering a diverse set of factors that can represent the innovativeness level of a country, this research is not only able to measure the effect of innovativeness of a country on the EV market but also how an innovative environment influences the purchase decision. Using the concept of symbolic motives and the subjective norms dimension from the TPB (Ajzen, 1985), people might perceive a pressure to purchase an EV. The concept of symbolic motives suggests that people acquire products which they can use to express themselves. Hence, based on this concept people might purchase an EV because they want to preserve their status as an innovative person who adopts new technologies rather quickly. Applying the dimension of subjective norms, it can be argued that in an innovative environment, people might feel a social pressure to behave innovative as well and thus purchase an EV. Hence, this research also entails a theoretical contribution. Significant test results of this determinant, as presented in Chapter 7, have validated the findings of previous research. Although, it is questionable whether the marginal effects represent the precise influence of an increase in the innovativeness level since this determinant is a psychological factor and no 100% objective measurement method of a psychological factor exist, it is nevertheless possible to conclude that innovativeness exhibits a sizeable effect on the market.

By carrying out a moderator and mediator analysis between wealth, innovativeness and the EV market, this part of the doctoral dissertation also contributes to the stream of literature that deals with how wealth indirectly influences the adoption of new technologies. While for the moderator analyses it is hypothesised that wealth is a necessary requirement to be able to afford such a vehicle and innovativeness reinforces the desire to purchase an EV, in the mediator analysis it is assumed that wealth directly influences the level of a country's innovativeness. Although the analysis of the moderation effect of innovativeness could not provide explicit evidence for this hypothesis, the possibility of a significant influence should not be ruled out, as the considered sample size is rather small. In contrast, signifi-

cant findings from the mediator analysis provide evidence for the indirect effect of wealth on the EV market through country innovativeness. Hence, country wealth plays an even more important role than initially expected. Different practical implications can be derived from the findings and are discussed in the discussion of the results in Chapter 7.4.6.

1.2.3 The Efficiency of Electric Vehicle Subsidies: A Study of the European Market

Although considered to be not as sustainable as the two intrinsic motivators discussed above, subsidies are a great policy measure to accelerate the diffusion of an innovation, especially in the early years of a product (Sierzechula et al., 2014). According to the DOI theory, the diffusion of an innovation accelerates the more the general population gets in contact with the product and the less risky they perceive the technology to be. This is due to doubts regarding the usefulness of the product and lack of opportunities to experience them if a product only diffuses slowly (Rogers, 2003). The initial years after market introduction are quite essential for the diffusion of a product as they often decide whether this technology remains on the market. In cases where innovations are supported early on by a large group of customers the product has better chances to survive on the market as the innovation becomes more and more visible to other people and could reduce the risk perceived by later adopters (Rogers, 2003; Plötz et al., 2014; Jenn et al., 2013). Furthermore, the revenues from early buyers could be used to reinvest into research and development, which could help to decrease the price of a product and make it more competitive.

To accelerate the diffusion of a new technology, especially in the critical first years, it thus makes sense to reduce the perceived risk stemming from a product. Transferring the risk aspect on the EV market, infrastructural concerns and as with many new eco-innovations high prices (Berkeley et al., 2018) might lead to the decision to neglect the purchase of this vehicle. To accelerate the adoption of this vehicle type a tool governments can utilise is therefore to subsidise the acquisition of this product to reduce the perceived risk. As a consequence, it can be observed that a multitude of countries are subsidising the purchase of an EV. These subsidies can take on different forms and most broadly categorised into financial and non-financial incentives. Non-financial incentives are for example the access to

bus lanes or restricted parking areas. These types of incentives are however not considered in this investigation as they are commonly granted on regional level and this research is conducted on a cross country level. Hence, a focus is laid on financial incentives, which can also be further divided into different subcategories, in this thesis.

In contrast to the psychological factors, research on the influence of subsidies on the EV market on macroeconomic level already exists, it however still exhibits areas where further research is required. The analyses conducted in Chapter 8 is based on the work of Münzel et al. (2019) and extends it in multiple ways. First of all, since a new technology develops quickly, it is important to frequently repeat studies and check whether previously determined relationships still hold. Hence, one contribution of this investigation is the consideration of a more up to date data set that also includes observations from the economic downturn in 2020. In addition to that, a distinction between vehicle types is made in this analysis. Besides looking at the aggregated EV market, it also distinguishes between BEVs and PHEVs since it can be assumed that factors might exhibit a different influence depending on the specific vehicle type. For example, the purchase of a PHEV does not entail such a great behavioral change as it also incorporates a traditional fuel powered drive train. Moreover, in many countries subsidies are structured differently depending on the vehicle type. Lastly, this research extends Münzel et al. (2019) by also applying a different methodological approach in form of a dynamic panel data model. This provides insights about the actual marginal effects as standard panel data regressions might overestimate the influence of subsidies. This is because they fail to account for the natural diffusion of such an innovation.

The results of the analyses reveal that most of the assumptions are correct and a repetition of the study of Münzel et al. (2019) with its deviations was indeed beneficial. To briefly summarise the results, it is found that the influence of subsidies have decreased over the last years, the influence of subsidies differs between the vehicle types and a static panel data model fails to account for the natural diffusion of this product and thus overreports the influence of subsidies. Assumptions about the causes behind these findings and a more detailed discussion about the implications thereof can be found in the discussion of the results presented in Chapter 8.5.

1.3 Aims and Objectives

The aim of this dissertation is to identify whether the three factors environmental awareness, innovativeness and subsidies are driving factors of the EV market and if so to what extent they influence this market. By taking on a quantitative approach, especially for the psychological determinants, this study enters a new avenue of research strategy to circumvent the biases arising from the predominantly applied survey approaches that were mostly limited to the analysis of EV purchase intention behavior. Distinct objectives of analysing the three research questions can be derived from the discussion of results sections from each chapter. Overall, the objective of this doctoral thesis is to contribute to the research stream that is dedicated to finding the determinants of this important market.

1.4 Structure

After providing information about the importance of this doctoral dissertation as well as explaining the contribution, aims and objectives of this study in this chapter, the next chapter is dedicated to providing a comprehensive review of the relevant literature and summarising the status quo in this research stream.

In Chapter 4 my philosophical approach for undertaking research is explained and implications of this philosophy on the research strategy are briefly outlined. Moreover, Chapter 4 presents the data set with all considered determinants and sources that are employed throughout the analyses.

In Chapter 5 all methodological approaches that are used in the analyses are thoroughly explained.

Chapters 6, 7 and 8 represent the main part of this dissertation. Each of the chapters present the results of the formal investigations of the three research questions. Moreover, in these chapters discussions and implications for practitioners derived from the results take place as well.

This doctoral thesis concludes with chapter 9, in which the main findings and recommendations for future research are summarised once more.

1.5 Publications from this Doctoral Thesis

Parts of this doctoral dissertation are published in international peer reviewed journals. The systematic literature review presented in Chapter 3 was published in the journal *Finance Research Letters* (ABS 2) as:

- Austmann, L. M. (2020). Drivers of the electric vehicle market: A systematic literature review of empirical studies. *Finance Research Letters*, 101846.

Moreover, large parts of Chapter 6, which focuses on the influence of EA on the EV market, were presented at the *International Conference on Energy Finance* in Qingdao. Thereby, this research was recognised with the best paper award issued by the *Chinese Academy of Sciences*. Later this research was also published in the journal *Energy Economics* (ABS 3) as:

- Austmann, L. M., Vigne, S. A. (2021). Does environmental awareness fuel the electric vehicle market? A Twitter keyword analysis. *Energy Economics*, 105337.

Individual sections of these two publications also appear in other sections such as the *Introduction* and *Literature Review*.

A BRIEF HISTORY OF THE ELECTRIC VEHICLE MARKET

For the longest period of time in human history, animals were used as the predominant means of transportation. It is assumed that horses were first domesticated around 3,500 BC. Hence, for a long era the transportation mode of choice were horses, if someone wanted to travel faster than human pace. Only in the early 1800s, with the invention of the steam locomotive, an alternative to horses was first developed (The British Museum, 2012). Although, the locomotive at that time presented a great alternative for travelling longer distances, it entailed different downsides in regard to the individual mobility such as the lack of flexibility due to predetermined routes or travel schedules. Consequently, the development of the automobile was an important invention that was eventually able to replace horses as the predominant means of transportation by simultaneously maintaining individual mobility advantages. When considering for how long humans depended on horses, the invention of the automobile in the year 1769 can be considered quite recent (Cromer et al., 2021). Even more recently, the mobility market is exhibiting a further push in a new direction. While the internal combustion car was for many years seen as an excellent solution for individual mobility, the call for more sustainable options has given rise to the electric vehicle market. Interestingly, this is not the first time electric vehicles have been proposed as an individual transportation mode. To further explore the development of this vehicle type on the

market, this chapter aims to briefly summarise the history of the EV market. For this purpose, the history of this market is divided into five time periods.

2.1 The Invention of the Automobile

Interestingly, the first car was not as many people would assume driven by a fuel based propulsion system but by steam (Cromer et al., 2021). Moreover, even electricity powered vehicles preceded the invention of gasoline dependent cars. Indeed the electric vehicle was invented more than 50 years before the first internal combustion car was developed by Carl Benz in the year 1886 (Vattenfall, 2020). Different sources accredit the invention of the electric vehicle to the Scottish inventor Robert Anderson in 1832 (Department of Energy, 2014; Vattenfall, 2020). His electric car incorporated a disposable battery to power the motor. The battery in turn was powered by crude oil to generate the required electricity. Incorporating this propulsion system the vehicle recorded a speed of about 12 kilometers an hour (Vattenfall, 2020). Before Anderson started his endeavours of developing a functioning electric carriage, different inventors from Hungary, Netherlands and the US, however, already built small scaled electric cars (Department of Energy, 2014). Consequently, the invention of the first electric vehicle cannot exclusively be assigned to Robert Anderson.

Although Anderson presented his EV in 1835 at an industry exhibition (Vattenfall, 2020), the first practical EVs, meaning the first EVs with reusable batteries, did not enter the market until after 1880. At that time, the invention of a practical electric vehicle by the French inventor Gustave Trouvé became possible due to the invention of a rechargeable lead-acid battery by French physicists Gaston Planté and Alphonse Faurue. In 1881, he used the rechargeable battery to power a small electric motor that was incorporated in a tricycle (Desmond, 2007; Cromer et al., 2021). Only a few years later, further electric cars were also developed by the English inventor Thomas Parker in 1884 as well as the German engineer Andreas Flocken in 1888 (Schoppert, 2017; Ernst, 2016). In the United States of America, the first electric car was built by William Morrison in 1890 (Department of Energy, 2014).

2.2 The Up-rise of the Electric Vehicle Market

The early up-rise of the automobile was driven by the desire to replace horses as the main transportation mode in the cities. People anticipated that with the transition to the automobile, problems such as noise, traffic congestion and accidents that accompanied the use of horse-drawn vehicles would be solved or at least decline. Although, as commonly known, cars did not provide a sustainable solution for these issues, they were nevertheless tolerated as they helped the cities get rid of the horse manure problem (Standage, 2021).

In the early years of the automobile market, EVs provided different distinctive advantages compared to their steam and gasoline counterparts, explaining their popularity in these years. Most of these advantages are concerned with the higher convenience the propulsion system offered. EVs were known for their higher comfort as they ran smoother and their motors were less noisy and did not emit smelling pollution the way gasoline vehicles did. Furthermore, EVs incorporated particular advantages regarding the starting of the engine. While an EV was able to start immediately, a gasoline vehicle had to be started manually with an hand crank and a steam powered vehicle required an up-heating time of the engine of up to 45 minutes in cold temperatures. Another big advantage of the EV in terms of comfort was that it did not require manual gear changes which were especially difficult in the first combustion cars (Department of Energy, 2014; Vattenfall, 2020; Cromer et al., 2021). Due to its simplicity in operation and the fact that fewer materials were required for the motor, an EV was considered to be not as prone to break down as an ICC (Gold, 2020; Standage, 2021). Consequently, by the turn of the century 38% of the vehicles in the US were powered by electricity and only 22% by gasoline (Standage, 2021).

The fact that more people obtained access to the electric grid in the 1910s, which enabled them to charge their cars at home, further contributed to the attractiveness of the EV. Another circumstance that has helped the acceptance of this vehicle type was the deficient road network outside of cities at this time. Cars were therefore predominantly used within a city and therefore limited the required travel distance, which mitigated the issue of the shorter driving ranges of EVs (Department of Energy, 2014). Even the well known inventor Thomas Edison was an advocate for the EV. He founded the Edison Storage Battery Company in 1901 and developed a nickel-iron based battery, which did not require maintenance and overcame the

short lifespan of the former battery models (Gold, 2020). In a different endeavour, around the year 1914, Thomas Edison started a collaboration with the famous car manufacturer Henry Ford to develop a cheap EV. However, this project eventually failed (Standage, 2021).

2.3 The Fall of the Electric Vehicle Market

Just before the 1920s, the electric vehicle lost its momentum and started to only play a niche role in the automobile market. This development was a result of preceding events and innovations which made the ICC a more attractive alternative. First of all, while ICCs became cheaper over the years, the price of an EV even increased. In comparison, a gasoline car was with 650\$ more than 1,000\$ cheaper than an EV, which sold for about 1,750\$ in the year 1912 (Department of Energy, 2014). Interestingly, although Ford worked on developing an affordable EV, his mass produced Model T was a crucial factor for the doom of the EV (Department of Energy, 2014; Gold, 2020). The invention of the assembly line by him in 1913, led to an even further reduction of the price of the Model T, thus making EVs even less competitive. When Ford stopped to produce the Model T in 1927, its price had decreased to 290\$ (History.com Editors, 2018, 2020).

Besides the substantial improvements in price of the ICC, another important invention significantly improved the comfort of this vehicle type. This invention was the electric starter for gasoline cars by Charles Kettering in 1912. The electric starter made the manual, labor intensive but also dangerous starting procedure with a hand crank obsolete, thus improving the handling of fossil fuel driven cars (Department of Energy, 2014).

The last crucial development that should be noted is the improved road network in the 1920s. During that time cities became better connected which increased the need for cars that were able to travel greater distances. As EVs exhibited a comparably short driving range and required a lot of time to recharge, this vehicle type turned out to not be the ideal transportation mode for exploration endeavours (Department of Energy, 2014). Moreover, rural areas were only poorly if at all wired with electricity in the US at that time, limiting the usability of EVs mostly to cities. The soaring market development of the ICC was fostered by the discovery of large petroleum reserves, reducing the fuel costs of this vehicle type (Department of Energy, 2014). Eventually, the combination of all these events led to the result that

the ICC established itself on and pushed the EV from the market. Over the next decades, the interest in EVs did not revive as the conditions for ICCs have rather improved with advancements in the technology and the access to cheap gasoline. A few attempts to establish EVs nevertheless took place during the second world war. For example, because of fuel scarcity in Britain, milk deliveries were made with EVs, which continued until the end of the 20th century (Cromer et al., 2021).

2.4 Sporadic Interest in the Electric Vehicle

Starting from the 1960s EVs have sporadically sparked the public's interest again, with different electricity propelled cars entering the market. A famous EV at that time was the Lunar Roving Vehicle. In the year 1971, this car was the first manned vehicle to drive on the moon (Matthe and Eberle, 2014). EVs, especially received greater interest in the 1970s during the energy price crises as a means of obtaining independence from oil imports. In the first oil price crisis for example, several Western countries were confronted with an oil embargo, imposed by the members of the Organization of Arab Petroleum Exporting Countries. The reason for this embargo was the support or perceived support for Israel in the *Yom Kippur War*. During the embargo the oil price increased dramatically, which exhibited a strong influence on the economies of the Western countries in particular and the world economy in general. This event pointed out the dependency on oil of these countries, leading to political actions with the scope to minimise this dependency (Knittel, 2014). For the automobile market, governmental regulations were developed that incentivised and forced car manufacturers to engage in EV research, resulting in the development of different EV models. One such regulation was for example launched in the US in 1976 and is called the *Electric and Hybrid Vehicle Research, Development and Demonstration Act, Public Law 94-413* (Chan, 2007). The goal of this Act was as discussed to foster the development of EV research activities. Another example of political interventions were the *Clean Air Act Amendment* (EPA, 2020) and the *Energy Policy Act* (U.S. Department of Energy, 2008) passed in 1990 and 1992, respectively. These acts were not only driven by the desire to reduce oil dependency but also to counteract environmental issues stemming from combustion cars.

The interest in EVs was, however, always only of short duration. In the 1970s, the performance of EVs was still significantly inferior compared to ICCs with most

of the available models recording a maximum speed of 45 miles per hour and a range of just 40 miles (Department of Energy, 2014). Hence, they did not reach a competitive stage. Moreover, car makers, at least in the US did not strongly engage in EV research or change their product lines (Standage, 2021). While, the performance of EVs slightly improved in the 1990s, with a range of approximately 60 miles, the production costs of these cars were still too high, limiting the competitiveness from an economic perspective. Furthermore, it is argued that during this time period, environmental concerns were not a priority. Consequently, the interest in EVs, at least from a consumer perspective, subsided due to low levels of environmental concerns in conjunction with low gas prices at this time. Although, EVs found no great consumer interest at that time, scientists continued researching and developing this vehicle type (Department of Energy, 2014).

2.5 A More Sustainable Interest in Electric Vehicles?

As previously described, the invention of the EV dates back more than 150 years and has frequently witnessed recurring interest over time. Therefore, it is surprising that a sustainable interest in this technology has just taken place at the turn of the century. In particular, according to the Department of Energy (2014) two events have played a decisive role for the recent uptake of this market. The first was the development of the first mass produced hybrid electric vehicle Toyota Prius. The Toyota Prius was developed in 1997 in Japan and found support early on. It is by many considered to be the embodiment of hybrid electric vehicles (Department of Energy, 2014; Ferris, 2019). Incorporating an electric as well as a combustion engine, the Toyota Prius, in contrast to vehicles that were predominantly powered by electricity, was not affected by the short driving range. Beneficial economic situations also took a large share in the rise of the Toyota Prius. One of the most important developments was the continuous increase in oil prices during the turn of the century. With a better fuel efficiency compared to traditional ICCs, the Toyota Prius therefore provided operational cost benefits to the customers, especially in the early 2000s and 2010s. Consequently, the Toyota Prius in all of its models and different generations has sold more than 15 million times worldwide, reaching its peak in sales in the year 2012. After, this time the sales volume has declined, which can be traced back to different reasons such as a decrease in the oil price or the

improved fuel efficiency of ICCs (Voelcker, 2018; Toyota, 2020). Touching upon the latter point, hybrid electric vehicles such as the Toyota Prius are just seen as a more fuel efficient ICC rather than an EV by a variety of people (Rezvani et al., 2015). Hence, the purchase of an hybrid electric vehicle might have made sense from an ecological perspective in the early years of the market but due to the improvements in the fuel efficiency of traditional ICCs, the significance of this factor may have diminished. Furthermore, vehicles that are predominantly powered by electricity have increasingly entered the market and outperform hybrid electric vehicles in terms of environmental sustainability.

The second event that has sparked interest in EVs is therefore unsurprisingly the announcement of a company, Tesla Motors, in 2006 to build a car that is entirely powered with an all electric drive-train that can reach a driving distance of more than 200 miles (Department of Energy, 2014). At this time Tesla was a start-up founded in Silicon Valley California in 2003. Nowadays it has developed to the highest valued automobile manufacturer in terms of market capitalisation, implying how the market predicts the future automobile industry to look like (BBC News, 2020). The announcement by Tesla to work on such a car, put other car manufacturers under pressure to also engage more strongly in the development and production of EVs. In the 2010s, Nissan for example introduced their model Leaf to the market. In contrast to the more luxurious Tesla sport cars, the Nissan Leaf was a more affordable alternative for the broader population. This vehicle has also been the most sold EV for a long time until it was superseded by the Tesla Model 3, which recorded a sales volume of more than 600,000 cars until the year 2020 after only 3 years since the model was available on the market (Kane, 2020). In addition, around 2011 the first plug in hybrid electric vehicle (PHEV) was introduced to the European market (European Environment Agency, 2016). PHEVs have the ability to drive a substantial distance with an electric engine, before switching to a combustion engine. Consequently, such a vehicle could be seen to be able to bridge the gap between the final step of switching from an ICC to a completely battery propelled vehicle. A PHEV is a means of allowing potential customers to build confidence in the technology and the infrastructure (Abnett and Carey, 2021).

Different external events, which were not controlled by the car manufacturers themselves have also helped the recent up-rise of the market and allow the conclusion that the interest in EVs can be considered more sustainable. First of all,

based on different treaties which focus on saving the environment as described in the preceding chapter, the goal of carbon emission reduction became and still is a central point in politics of a multitude of countries. Consequently, the development and acquisition of this vehicle type is financially and non-financially supported by a lot of countries. Such measures also reflect the increasing level of environmental concerns in comparison to previous decades. To mention just a few examples of governmental support, Tesla Motors was for example supported with a \$465 million loan from the US government for the construction of a manufacturing site in California (Department of Energy, 2014). Another example is the *European Green Cars initiative* brought into being by the European Commission, the scope of which was to provide grants for research and development and demand side incentives like tax reductions (European Commission, 2009b). With increased engagement in research and development, cost reductions of the vehicle were achieved in the last years. This leads to the result that EVs are approaching cost parity with ICCs (Boudway, 2020). Furthermore, improvements in batteries could lead to a farther driving range, reducing range anxiety concerns, thereby making EVs even more competitive. Moreover, the subsidised installation of a charging infrastructure is another example of governmental support (Department of Energy, 2014). With the expansion of the charging infrastructure, the range anxiety concerns of the people can be even further reduced. This is a major point. As discussed above, in the past range anxiety was one of the key factors that prevented the breakthrough of the electric vehicle.

Based on all the above, it can be concluded that due to improvements in the EV technology and infrastructure, support from governments, increasing environmental concerns compared to the last decades and reduction in costs of this vehicle type, the interest in EVs is more sustainable than it has ever been in history.

LITERATURE REVIEW

This chapter is dedicated to providing a comprehensive review of the existing academic literature in the field of electric vehicle adoption, relevant to this thesis. The purpose of a thorough literature review is to reflect the already obtained knowledge and to identify potential research gaps. Consequently, the literature review is an essential part of this thesis to assure that a contribution to academic knowledge can be generated. As EVs are currently of interest to a variety of research strands, the academic boundaries of the reviewed literature initially needs to be determined. This review focuses on the strand of literature in the subject areas finance, business and economics. A further review restriction is made by only considering studies that have investigated passenger cars.

3.1 Defining Electric Vehicles

Although, most people would claim to have a general understanding of what an EV is, some properties of this vehicle type are not as evident as one might initially expect. In particular, in this subsection the economic properties of passenger cars in general will be reviewed and an understanding what an EV actually is, will be provided. It is important to have a common understanding of this product as different products appeal to different customer groups and thus factors influencing their adoption vary. Moreover, one can find varying definitions of an EV in literature and practice. Hence, it is important to clarify which definition this thesis will apply.

3.1.1 Economic classification of the automobile sector

Although, it can be assumed that a general understanding of cars exists, a classification of this good from an economic perspective might not be as definite as initially assumed. However, an understanding of the economic properties of a product helps to apprehend and analyse the demand for the respective product depending on the market development (Mankiw and Taylor, 2012). Consequently, it can be of particular interest to determine the economic properties of cars as the focus of this investigation is laid on determining the driving factors of the electric vehicle market. Therefore, in this section the car as a product is classified based on three common economic classification approaches. These classification systems are not conflicting but should be considered as complementary. A distinction between internal combustion cars (ICC) and EVs in the classification will be made where appropriate.

Starting with the broadest classification, goods can be divided into consumption and investment goods. To decide whether a car is a consumption or a investment good, it makes sense to initially define and explain the differences between these groups. Consumption products can be defined as any product or service that consumer can buy for their own use (Cambridge Dictionary, 2021b). An investment good, also known as capital good, on the other side is defined as any product that is used to produce the final product for consumption (Cambridge Dictionary, 2021a). Based on these definitions the goods distinguish themselves from each other regarding their aspired target group and their order in the production process. While an investment good is used to create new products, a consumption good is the final product that a consumer actually uses. Cars and especially passenger cars can therefore most likely be categorized as a consumption good. Consumption goods, however, can further be divided into consumer durables and actual consumption goods. The difference between these subcategories is the duration for which a consumer can use a product. While actual consumption goods can only be used once, consumer durables can be used over a longer period of time. As cars can be used more often than once, their final classification would be a consumer durable (Britannica, 2021). Thereby, it is irrelevant whether the car is a traditional ICC or an EV.

As cars have been determined to be a consumption good, further more refined categorization of consumption goods can be made. Another way to categorize goods can be made based on the characteristics of excludability and rivalrousness

(Mankiw and Taylor, 2012). Excludability refers to the situation when people can be prevented from buying a good. Rivalrousness refers to the situation when the consumption of a good affects the availability of this good for other people. Based on these two characteristics, it can be distinguished between four different kinds of goods. These are Private Goods, Public Goods, Common Resources and Club Goods. Figure 3.1 depicts how these four goods differ based on the the characteristics excludability and rivalrousness.

Figure 3.1: Rivalrousness-Excludability

	Excludable	Non-Excludable
Rival	Private Goods	Common Resources
Non-Rival	Club Goods	Public Goods

Note: Illustration based on Mankiw and Taylor's 2012 illustration of Rivalrousness and Excludability.

A *private good* is excludable as the owner of the product can prevent other people from using it. Furthermore, it is rival as a private good only exists once and the owner is entitled to full possession of it.

Public goods are not excludable and not rival. Thus people cannot be prevented from the usage of a good or service. Furthermore, there is no scarcity of this good or service, which means that the usage of this good does not result in the unavailability of the product for another person.

Common resources are not excludable but rival. Common resources are goods that nobody can claim possession of wherefore everyone could potentially use it. These products are however limited in number. Thus a person's usage of this product will take another person's ability of using this product.

Club goods are excludable but not rival. Mankiw and Taylor (2012) also call this group natural monopolies. Thus this group of products could be accessible to all without a reduction of resources when being used by a person. However, the access of this product or service can be prevented for people. For example, when the access

to a product is linked to joining a club, a possible barrier to obtain usage over this good could be membership costs.

Considering these four categories, cars can be assigned to the group of private goods. When a person purchases a car, he or she can exclude other people from the use of this car. Furthermore, a car can only be owned by a single person, thus making it a rival good. Hence, a car falls into the same classification as the majority of products available on the market. Consequently, the prices are largely determined by basic economic principles and market forces such as supply and demand. Therefore, it can be assumed that the principles of income- and price elasticities also apply to cars (Mankiw and Taylor, 2012; Summary and Henry, 2013).

As a result, the last categorization that can be made is based on the response of the demand of a product to changes in income or the price of the product itself.¹ Therefore, the elasticity is the focus of this categorization. Goods can broadly be categorized into two types, namely normal and inferior goods. They distinguish themselves based on the sign of the slope of the elasticity (Mankiw and Taylor, 2012).

In economics the demand of a good is traditionally considered to increase when prices decrease or income increases. Consequently, this group of products is termed normal goods. Normal goods can further be divided into two subcategories, necessity and luxury goods. The difference between them is the level of elasticity. In contrast to necessity goods, luxury goods are highly elastic as they are not considered to be essential. In particular, this means that the demand of luxury goods reacts more sensitive to changes in price or income, because humans will initially cater to their basic needs such as buying food or spending money on heating.

In contrast to normal goods, inferior goods exhibit a negative income elasticity. When people have more money to spend because of an increase in income, they tend to switch to substitute products that provide them with higher convenience. A commonly used example to illustrate this behavior are bus and taxi rides. When somebody has more money available he or she is more likely to take a taxi and pay more for the transportation instead of using a bus. When considering price rather than income elasticity, the equivalent of an inferior good is also known as a substitute good. When a price of a good that can easily be replaced by another

¹While the relation between demand and income is referred to as income elasticity, the relation between demand and price is known as price elasticity.

product is increasing, people tend to substitute the product with the cheaper one. In economics, the relationship between two products where the demand of one product increases when the price of the other product goes up can be measured with the so called *cross price elasticity of demand*. This concept allows the determination of the percentage change in the demand of a product, if the price of the substitution product changes. In case the products are substitution goods for each other, the cross price elasticity is positive exhibiting higher values the better one product can replace the other. In contrast, when products are used supplementary, the cross price elasticity will be negative as an increase in price will also result in a lower demand for the other product (Mankiw and Taylor, 2012).

It should be noted that the elasticities of a product are different for each individual. While for example bread is to one person an inferior good, it could be considered a normal good by a person with a different income level (Mankiw and Taylor, 2012). This can at least partially depend on a person's income level. However, for most products and individuals the classification of products are the same.

As identified in the previous categorization, cars can be classified as consumer durables. Consumer durables are generally associated with higher price elasticities than consumption goods because the purchase of a consumer durable is easier to postpone. Moreover, an individual might decide to repair an old product instead of replacing it with the purchase of a new one if the prices are too high (Anderson et al., 1997; Mankiw and Taylor, 2012). Hence, it can be assumed that cars in general exhibit a high price elasticity as for most people they are not considered an essential good. Furthermore, as discussed above, products that can easily be substituted are more price elastic. Since the purchase of a car can for example be substituted by public transportation or even within this product type by the purchase of a different brand or model. This effect even further amplifies the elasticity of this good. Subsequently, it is not surprising that different researchers have uncovered a relatively high price elasticity of the demand of cars and employ automobiles as an example for elastic products (Anderson et al., 1997; Fridstrøm and Østli, 2021).

A high sensitivity to changes in price and income of the demand of cars also has relevant implications for this thesis. In particular, this is an important aspect for the development of the EV market as EVs are currently in general more expensive than comparable ICCs. Thus, a change in price or income can lead to significant

movements in the market share of EVs and ICCs.

Moreover, considering that traditional fuel cars and vehicles that are powered by an electric drive train are products with a high potential to substitute each other, the *cross price elasticity* of the products might also play an important role for the demand of EVs and likely contributes to the elasticity of this product. An increase in price of traditional fuel cars can theoretically result in a substitution effect of EVs for ICCs and foster the development of the market. In a study focusing on the Norwegian automobile market and taking advantage of the high ownership rate of EVs in this country, Fridstrøm and Østli (2021) have proven the high degree of substitution between EVs and ICCs.

3.1.2 Vehicle Types

Passenger cars can be differentiated in several possible ways. They can for example be categorized based on size, price, brand or purpose (e.g. sports car, pickup truck). As the focus of this study, however, lays on EVs it makes sense to differentiate cars based on the propulsion system.

In terms of the propulsion system, the automobile-sector has not been considered innovative for many years as ICCs have dominated the market for more than 150 years. The interest in other than fossil fuel dependent engines, has sporadically increased in the history, however until recently a different kind of engine could never reach a competitive stage and prevail on the market (Plötz et al., 2014). Often the research in new engine systems has witnessed increasing interests in times of oil price crises or environmental issues such as smog occurrences. With the disappearance of these immediate issues, the interest in different propulsion has however also quickly subsided. Consequently, most car manufacturers focused on optimizing the existent engines by minimizing the CO_2 emissions rather than developing an entirely new engine system. In the last two decades a new and maybe more sustainable interest in different propulsion system has arisen. Driven by environmental concerns, governments have increased spendings in the development of alternative propulsion systems and infrastructure (Morton et al., 2016). As pointed out previously, cars are traditionally fueled with petroleum, wherefore cars that are powered with a different fuel type are often termed Alternative Fuel Vehicles (AFV).

Therefore, a broad categorization can be made by distinguishing between ICCs powered by traditional petroleum fuels and AFVs. There are however different

definitions of AFVs. The U.S. Energy Information Administration (2019) for example defines AFVs as any vehicle that is primarily powered by any other fuel than petroleum. Thereby, a vehicle will also be classified as an AFV if it incorporates an additional petroleum powered engine, as long as the primary source of power is different. Vehicles that can therefore be classified as an AFV are for example powered by biofuel, ethanol, natural gas or electricity. When considering cars that incorporate an electric motor, however, according to this definition not all of these vehicles directly qualify as AFVs. The main propulsion of a hybrid electric vehicle (HEV) for example is a traditional petroleum engine. Therefore, HEVs are not included in this category of vehicles. Another definition has been established by the U.S. Department of Energy (2020b). They define AFVs as:

“A dedicated, flexible fuel, or dual-fuel vehicle designed to operate on at least one alternative fuel.”(U.S. Department of Energy, 2020b, p. n.a.)

Thus, in contrast to the former definition, HEVs can according to this definition also be considered as an AFV.

As discussed above, electricity powered vehicles can be classified as a subgroup of AFVs. Thereby, it can be distinguished between different kinds of vehicles which differ in regard to their propulsion technology. In particular, previous literature has summarized hybrid electric vehicle, plug-in hybrid electric vehicle, extended-range battery electric vehicle (E-REV) and battery electric vehicle under the term electric vehicle (EV). While the first three vehicle types incorporate next to an electric engine also a traditional combustion engine, a BEV solely relies on an electric power train. HEV, PHEV and E-REV differ based on the importance of the electric engine in the vehicle. The vehicle type that relies the least on the battery engine are HEVs. HEVs do not provide the ability to charge the battery with a plug-in charger but load it with energy generated during the break process or from the petroleum engine. Consequently, several researchers do not consider HEVs as an EV but as a more fuel efficient ICC (e.g. Schuitema et al., 2013; Rezvani et al., 2015) since “all the HEV’s energy comes originally from the liquid fuel” (Rezvani et al., 2015, p. 123).

PHEVs and E-REVs both incorporate an electric and an internal combustion engine but also provide the ability to be charged via plug-in chargers. Therefore, they do not necessarily rely on the combustion engine. The two vehicle types distinguish themselves based on the range the car can travel using the electric motor. The E-REV is considered a further development of the PHEV and therefore

offers a longer all-electric driving range (Rezvani et al., 2015). As both vehicle types solely differ based on the driving range of the electric motor, E-REV can be considered a subgroup of PHEVs (cf. U.S. Department of Energy, 2021). Hence previous research often does not distinguish between these two types. This research therefore follows the customs of previous research and summarizes PHEVs and E-REVs as PHEVs.

Passenger cars are classified as BEVs when they solely rely on an all electric drive-train. Consequently, they do not incorporate a combustion engine that can load the batteries and therefore require the electricity grid to recharge. With a larger battery capacity compared to PHEVs, BEVs exhibit the largest driving range under an electric motor (Schuitema et al., 2013).

Next to BEVs there is also another vehicle type that can be considered to run on an all-electric drive train. Specifically, these are Fuel cell electric vehicles (FCEV) (U.S. Department of Energy, 2020a). FCEVs are fueled with hydrogen which reacts with oxygen in a fuel cell. In this process electricity is generated that can charge the batteries in an FCEV (U.S. Department of Energy, 2020a). When comparing BEVs with FCEVs each of these technologies have their specific advantages and disadvantages. The biggest advantages of the FCEVs often highlighted are related to its refuelling similarities with traditional cars and the driving range (Graham, 2020). FCEVs can be refueled within four minutes and are able to drive distances of more than 480 kilometres (U.S. Department of Energy, 2020a). The driving range and recharging pace is considered to be one of the major shortcomings of BEVs but anticipated to significantly improve in the next years (Volkswagen, 2016). Moreover, BEVs in comparison to FCEVs provide the possibility to be recharged at home. Other important advantages of BEVs are for example the cheaper price as well as the already established infrastructure of this vehicle type (Graham, 2020). While there is no consensus which vehicle type is superior, several industry experts point out the higher efficiency in terms of energy consumption as well as the lower costs of this technology (Volkswagen, 2016). In particular, a study conducted by the consultancy firm Horváth & Partner has compared the energy efficiency of BEVs and FCEVs (Voggenreiter, 2020). Energy efficiency in this study is determined by how much energy is lost in the processes from the source of the energy to the final transition that powers the wheels of a car, also known as *Well-To-Wheel analysis*. The study determines that for the same distance, a hydrogen fueled vehicle requires two to three times more energy than a BEV. To be precise, while

BEVs exhibit an electricity efficiency between 70-80%, the efficiency of FCEVs lays in the range of 25-35% (Voggenreiter, 2020). A BEV loses most of its electricity during its conversion to propel the electric motor (18%). Another 8% is lost in the preceding process of transport and storage. The FCEV on the other side, already loses most of the energy during the electrolysis process (45%), i.e. the generation of hydrogen. Furthermore, the transformation of the hydrogen back into energy in the fuel cell requires additional energy. Of the remaining 55% of energy, more than half is lost during this process (Voggenreiter, 2020; Volkswagen, 2016). These findings are further supported by a study conducted by the European Federation for Transport and Environment (2021). Additionally, the European Federation for Transport and Environment (2021) claims that e-fuel propelled vehicles such as hydrogen FCEVs will remain more expensive than BEVs, which is caused by the inefficient use of the electricity. Consequently, these industry experts come to the conclusion that hydrogen and therefore FCEVs cannot establish themselves on the market but recommend the application of this technology rather in the shipping, aviation and heavy-duty transport industry (European Federation for Transport and Environment, 2021). In addition to the arguments just described, FCEVs are neglected in this investigation, as with 23,354 vehicles worldwide in 2019, they only play a niche role in the market (International Energy Agency, 2020a). This becomes even more evident when considering the low development of the FCEV infrastructure. In the European Union, only 113 hydrogen fueling stations existed in 2019 (European Alternative Fuels Observatory, 2020). It can, therefore, be concluded that this technology is in its beginnings and could play a more significant role in later years.

Looking at previous literature there is no consensus on what can be defined as an EV. While there are some researchers that include HEVs in the category of EVs (Chen et al., 2015; Kumar and Alok, 2020), other argue that an HEV is just a fuel efficient combustion car (Schuitema et al., 2013; Rezvani et al., 2015). The authors support their claims as in contrast to PHEVs and BEVs, the purchase of an HEV does not require substantial changes in refueling behavior and the handling of a car overall. Rezvani et al. (2015) for example argue that with the purchase of a new vehicle technology such as PHEVs and BEVs, consumers have to adopt their driving behavior to the new requirements of these vehicle types. Hereby, the authors especially point out the significant changes in regard to the refuelling of PHEVs and BEVs. Since the recharging process of these vehicle types requires

more time than the traditional refueling with petroleum, owners need to plan their travels ahead and learn to reload their vehicles when they are not in use (Rezvani et al., 2015). In relation to the recharging, Rezvani et al. (2015) emphasized the potential role of range anxiety and the influence on BEV and PHEV adoption. They pointed out that the lack of public charging points, especially in the early years of the market, the time the batteries require to recharge and the driving range are shaping the range anxiety of potential customers. Consequently, owners of these vehicle types need to plan their route ahead, especially for longer journeys. These perceived barriers, however, can diminish as technology advances.

The decision to not consider HEVs as a vehicle type that falls under the category of EVs can further be supported when looking at definitions of EVs. The Bundesministerium für Umwelt Naturschutz und nukleare Sicherheit (2020) for example defines EVs as follows:

“Electric mobility comprises all street vehicles that are powered by an electric motor and primarily get their energy from the power grid.”

According to this definition HEVs will not be classified as EVs as their main propulsion technology depends on a traditional fuel dependent internal combustion system. This research takes on the same understanding of EVs as Schuitema et al. (2013) and Rezvani et al. (2015) that EVs can be charged externally from the electric grid and therefore for the remainder of this thesis the term EV will encompass the vehicle types PHEVs and BEVs. This is of particular importance for this investigation as the reasons for the purchase decisions can alter based on the considered vehicle type.

3.2 Drivers of the Electric Vehicle Market

While the previous section has focused on defining EVs and determining their properties in an economic context, the determinants of the EV market investigated in previous research will be reviewed in this subsection.

3.2.1 Theoretical background

Two excellent reviews of the most commonly applied theoretical backgrounds previous literature has used to explain the drivers of electric vehicle adoption have

been executed by Rezvani et al. (2015) and Adnan et al. (2017). Nevertheless, for the sake of completeness and to provide a self-contained document, an overview of the most important theories in this stream of literature will also be provided at this stage. The review, however, will be kept brief and focuses more on the theories themselves and how they can be linked to the EV market rather than how different researchers have applied them.

3.2.1.1 Theory of Planned Behavior

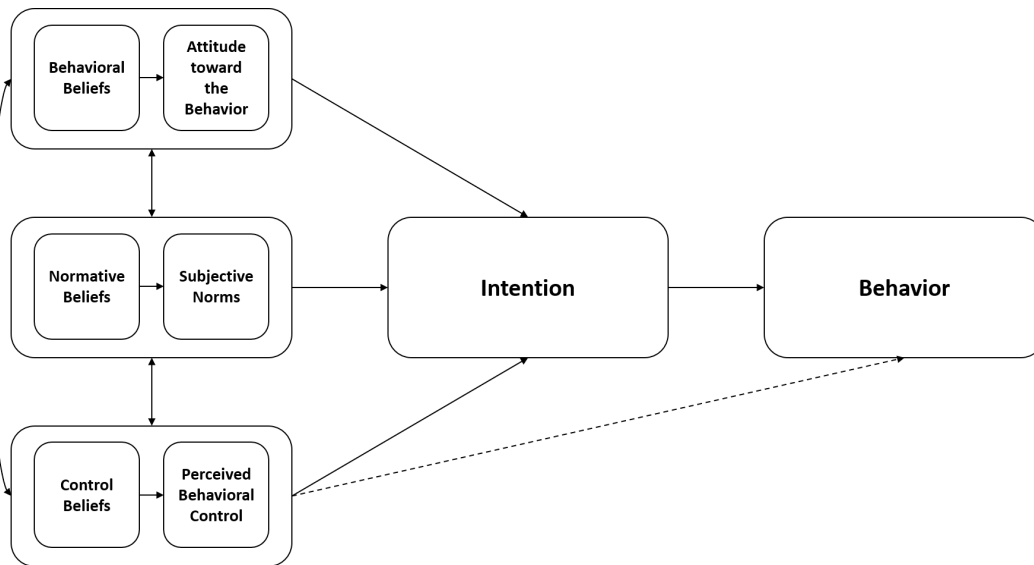
The theory of planned behavior (TPB) was established by Ajzen (1985) and is an extension of the theory of reasoned action (TRA) developed by Fishbein and Ajzen (1975, 1981). It supplemented the TRA by adding a perceived behavioral control dimension. The TPB focuses on explaining the relationship between a human's motivation and his or her behavior. Thereby, it does not only serve to enhance the understanding why an individual engaged in a particular behavior but can also be used to predict future behavior.

The underlying assumption of this theory is that people make conscious decisions that rely on information and take the consequences of their actions under consideration. The structure and the components of the TPB are illustrated in Figure 3.2. According to the TPB a person's behavior can ultimately be predicted based on its behaviour intention. The intention represents the motivation of a person to engage in a behavior. Consequently, the more motivated a person is to engage in a behavior the higher the likelihood of the exertion of this behavior. More interesting for the understanding of how an individual's behavior is influenced, however, are the three different sets of determinants that affect an individual's behaviour intention (Ajzen, 1991; Boslaugh, 2019). These are *attitude toward the behavior*, *subjective norms* and *perceived behavioral control*. The *attitude toward the behavior* is shaped by all the individual's beliefs and therefore encompasses all positive and negative beliefs towards a certain behavior. Depending on whether positive or negative beliefs outweigh, the individual exhibits a positive or negative attitude toward the behavior. Subjective norms can be understood as the social pressure the individual expects to face when engaging in the respective behavior. The social pressure, which can be interpreted as the normative beliefs in Figure 3.2, is predominantly exercised by the group of people that is important to the individual. The last group of determinants is *perceived behavioral control*. This group comprises factors that could potentially hinder an individual to engage in the

actual behavior. These factors could be for example money, skills or time. Perceived behavioral control factors are also the only group of factors that do not only influence the behavior intention but also have a direct effect on the eventual behavior (Ajzen, 1991; Rezvani et al., 2015; Boslaugh, 2019).

All three groups of predictors also exhibit interaction effects. For example, an individual's social environment could influence its own beliefs and vice versa.

Figure 3.2: Theory of Planned Behavior



Note: Illustration from Kan and Fabrigar (2017) of the Theory of planned behavior developed by (Ajzen, 1991).

In regard to the EV market, researchers have often applied the TPB to explain the adoption of EVs (e.g. Wang and Dong, 2016; Zhang et al., 2018b; Tu and Yang, 2019). Due to the relatively small ownership rate of EVs, researchers mostly investigated what factors influence the intention to adopt an EV by means of surveys, as by employing this approach it is easier to obtain a sufficient sample size (Jensen et al., 2013). Since, according to the TPB, the behavior intention directly influences the eventual behavior, the researchers used their findings regarding purchase intention to draw conclusions on EV adoption. There is a multitude of studies that have focused on analysing consumer attitude towards EV adoption (Egbue and Long, 2012; Yadav and Pathak, 2016; Wang and Dong, 2016; Wang et al., 2016). One of the most commonly applied approaches to assess the attitude of individuals towards EV adoption is to measure the attitude towards EVs in general or potential adoption barriers as well as drivers and how they are perceived by potential consumers. Adoption barriers and drivers include various factors

and must be evaluated subjectively by each individual. They can be for example reflected by certain attributes of EVs such as price, driving range or technology of this type of vehicle or other factors such as charging infrastructure (Moons and De Pelsmacker, 2012). The influence of subjective norms on the intention to adopt EVs has witnessed less but also considerable academic interest. Thereby, the relationship between subjective norms and EV adoption has been measured in different ways. Applying surveys, researchers have for example questioned the survey respondents whether their purchase intention of an EV is influenced by the opinions or values of their families, colleagues or friends (Yadav and Pathak, 2016). Another approach of investigating the influence of a subjective norm factor is by looking at a neighbouring effect of EVs and executing spatial analysis. Using this approach, the researchers theorise that people's intention to adopt EVs is higher in regions with a higher EV ownership rate as they might be exposed to social pressure and are better able to familiarise themselves with this product (cf. Liu et al., 2017; Chen et al., 2015).

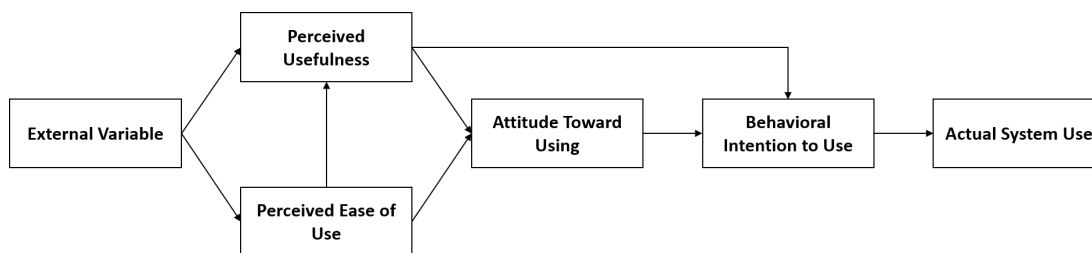
The last dimension of the TPB, is reflected by potential barriers that prevent people to adopt EVs. These can be for example the limited driving range of EVs and the higher purchasing prices in contrast to comparable ICCs. Thereby, the problem might arise that people cannot afford or use an EV as their commuting distance exceeds the driving range of the vehicle (Rezvani et al., 2015).

3.2.1.2 Technology Acceptance Model

Although, the technology acceptance model (TAM) has been developed to understand the important factors for the adoption of a new computer information system, it has also been applied to the EV market (e.g. Tu and Yang, 2019). The theory has been developed by Davis (1986) and is a modification of the TRA, adjusted to the case of computer systems. Consequently, several determining factors, which can be seen in Figure 3.3, in the process to adopt new information systems resemble the TPB. In particular the last three steps in the TAM correspond with the stages of attitude toward behavior, behavior intention and behavior already known from the TPB and can therefore largely be interpreted in the same way as in the previous paragraph. The refinement of this theory lies in the preceding stages. The TAM emphasizes the role of external factors and tries to provide a framework on how to analyse their influence on internal factors such as beliefs, attitudes and intentions. Davis (1986) introduces two beliefs in particular to the model which are influenced

by the external factors. These are the dimensions of *perceived usefulness* and *perceived ease of use*. Perceived usefulness is defined as the subjective valuation of an individual whether the use of a new technology improves his or her performance. The perceived ease of use dimension can be interpreted as the level of difficulty to adopt and use the new technology. In Figure 3.3 it can be seen that perceived usefulness and perceived ease of use are also interlinked. As can be seen from the direction of the arrow, it can be concluded that the effort somebody has to apply to learn or use a new system can also determine an individual's perceived usefulness of the system. While both perceived usefulness and perceived ease of use shape an individual's attitude toward a new system, the dimension of perceived usefulness also directly influences the behavioral intention to use the system.

Figure 3.3: Technology Acceptance Model



Note: Illustration by Davis et al. (1989).

As pointed out earlier, the TAM is in its structure similar to the TPB as it also incorporates the dimensions of attitude toward behavior, behavior intention and behavior. Consequently, it is of interest how the additional dimensions perceived usefulness and perceived ease of use are linked to the EV market. Starting with the dimension of perceived ease of use, per definition the difficulty of learning to handle and in general to operate an EV can be investigated. Research can for example be executed on the behavioral changes that a transition from an ICC to an EV requires. For example, as discussed in the previous section, an individual needs to adapt to a new charging behavior and more carefully plan its travels. These behavioral changes can be perceived as significant inconveniences and negatively associated with the effort to adopt an EV. On the other hand, an individual can for example perceive the improved acceleration as a positive factor, enhancing the convenience of an EV compared to an ICC. Thus, such a factor would improve the perceived ease of use (Plötz et al., 2014).

Not just advantages and disadvantages of an EV compared to an ICC can

influence a consumers perceived ease of use but also the existence of similarities. In a survey, Wang and Dong (2016) for example asked the respondents whether it would be easy for them to learn driving an EV and used the answers to draw conclusions on the perceived ease of use of EVs. Since EVs compared to ICCs do not have changed fundamentally in regard to the control systems, the driver does not have to adjust his or her driving style or develop new skills. Therefore, this factor neither presents a barrier nor an advantage to individual's for adopting an EV but can be perceived to increase the ease of use as no behavioral change is required.

The dimension of perceived usefulness in this context is concerned with the question whether an EV can improve an individual's perceived efficiency. The example from the previous section of the behavioral change in terms of charging the vehicle, does not only illustrate the influence of perceived ease of use on perceived usefulness but also proves to be an important factor for perceived usefulness analysed in previous research (Wang and Dong, 2016). IF the charging time of an EV is for example considered as too long for an individual, it does not only increase the effort to operate an EV but can also significantly limit the usefulness of this vehicle type when the individual has to commute long distances (Kumar and Alok, 2020).

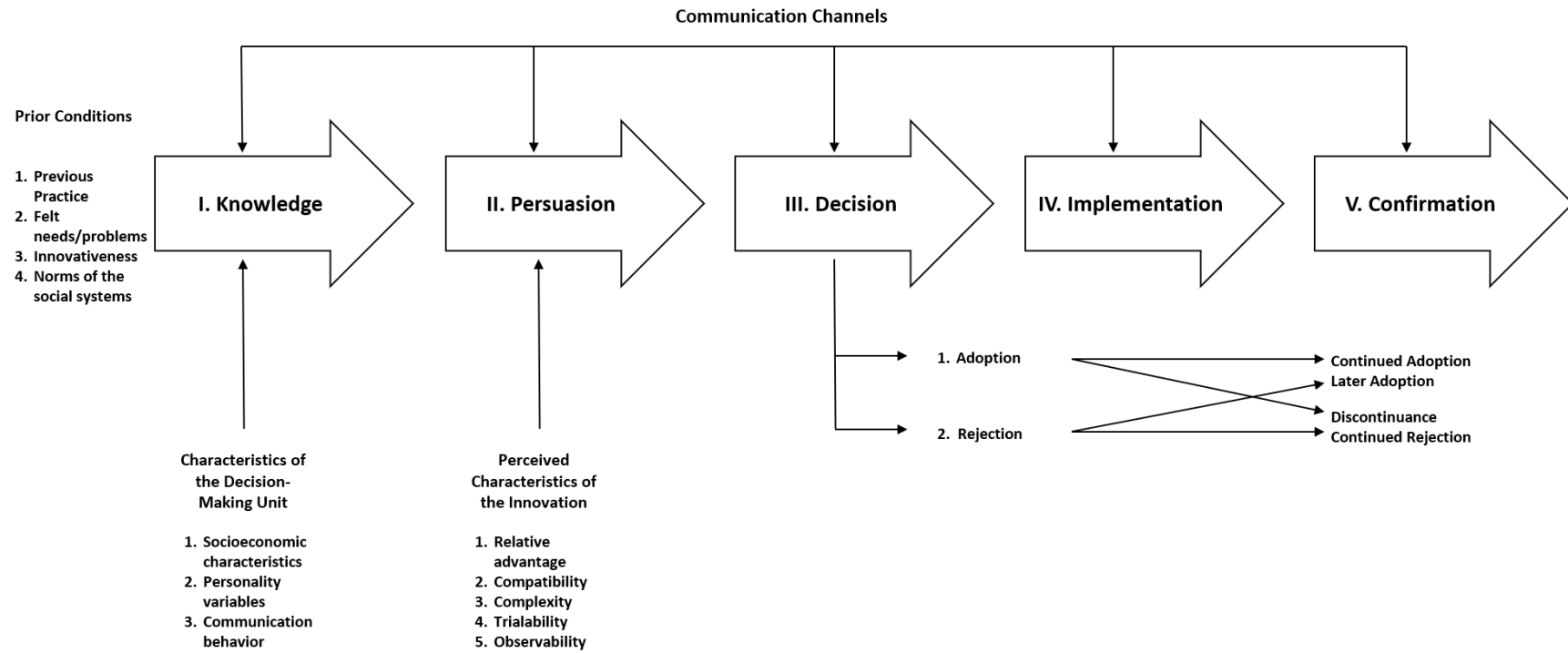
It should again be noted that each factor and its benefit or disadvantage as well as its importance is perceived differently by each individual. Eventually, an individual will sum up all the positive and negative factors of the dimensions perceived ease of use and perceived usefulness. Depending on what outweighs it will either exhibit a positive or negative attitude towards EVs.

3.2.1.3 Diffusion of Innovations

Diffusion of innovations (DOI) is a theory developed by Rogers (1962) and is concerned with the explanation and prediction of the adoption of an innovation by a society. It explains which factors influence the acceptance of an innovation, such as a new product, technology or idea, and provides insights into drivers and barriers of a successful adoption within a society. Rogers (2003) emphasizes the role of four elements in the diffusion process of a new idea as he defines the process as "... the process by which (1) an *innovation* (2) is *communicated* through certain *channels* (3) over *time* (4) among the members of a *social system*." (Rogers, 1983, p. 5)

The adoption of a new innovation can be explained by means of a five stage process (see Figure 3.4), which every individual usually needs to pass through.

Figure 3.4: The Innovation-Decision Process

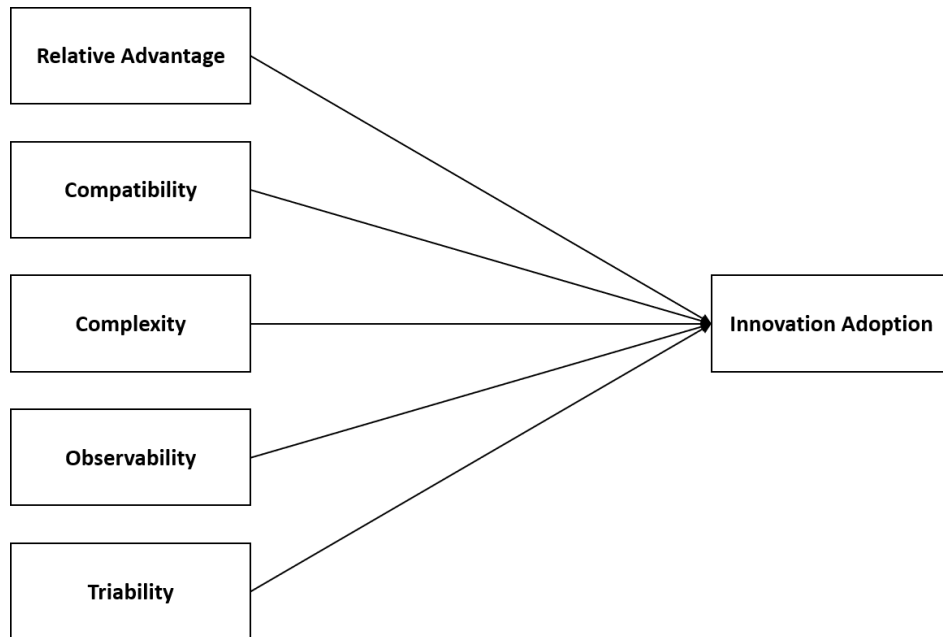


Note: Illustration by Rogers (2003).

The innovation-decision process starts with the individual's awareness of a product. It is the first sign of the innovation's existence that the person or decision-making unit notices. At this stage, the individual also starts to gain an understanding of the product. In the second stage the decision making unit has obtained knowledge of a few attributes of the new innovation and starts forming an opinion of the product. Thereby, five characteristics of the product, which each individual can perceive differently, are of particular importance as they shape the attitude towards the new innovation. These are, the relative advantage, compatibility, complexity, trialability as well as observability and will be discussed in more detail at a later point. In the decision stage, based on its attitude towards the innovation, the individual either adopts or rejects the new innovation. Hereby, it should be noticed, that in case the individual rejects the adoption of the innovation, it can still re-decide and adopt the innovation at a later stage. When the decision making unit adopts the new technology, it has to implement and use it as a consecutive behavior. Based on the experience that the individual collects with the innovation, the adoption decision will either be confirmed and the individual continues the use of the product or it discontinues the usage. This is reflected by the last stage of the process, which is termed confirmation (Rogers, 2003).

As previously discussed an important part of the innovation-decision process are the perceived attributes of an innovation. These will be briefly explained at this point, since they are important to shape an individual's attitude towards the innovation and therefore, the eventual adoption. A new innovation has to possess five characteristics to be successful and prevail on the market. These characteristics are relative advantage, compatibility, complexity, observability as well as trialability. Thereby, the level of how much a new idea or technology fulfills each characteristic differs depending on the individual.

Figure 3.5: The 5 Perceived Attributes of Innovation



Note: Illustration by Rogers (2003).

A new technology must provide advantages compared to the existing technologies on the market. Consequently, one of the attributes Rogers (2003) mentions is the relative advantage compared to existing solutions an individual perceives to obtain when adopting a new technology. Compatibility requires an innovation to correspond with the values and beliefs of an individual. Furthermore, it captures the consistency of previous experiences of the individual and to which degree it fulfils the purpose for which it was adopted. The characteristic complexity is similar to the dimension perceived ease of use from the TAM. It refers to the level on how difficult it is to handle the new technology. Observability in this sense can be interpreted as the level of how easily others can see what benefits the new technology provides. Lastly, trialability is the degree to which individuals can test the innovation before adopting it. Except complexity, a higher level of awareness of each of these product characteristics is in general associated with a higher adoption rate (Rogers, 2003).

The five characteristics are also commonly applied to analyse why people adopt EVs (e.g. Jansson, 2011; Peters and Dütschke, 2014; Petschnig et al., 2014). Thereby, EV attributes are for example considered that can function as surrogates for these factors.

The categories relative advantage and complexity are quite similar to the

dimensions perceived usefulness and perceived ease of use of the TAM. Sometimes researchers also replace them with each other. Peters and Düttschke (2014) in their study for example replaced complexity with ease of use, as ease of use is the positive equivalent to complexity. Consequently, the explanation of the characteristics in the EV context can mostly be derived from the previous subchapter and thus do not require further elaboration. However, it is important to mention that when comparing the definitions, relative advantage is broader defined than perceived usefulness. While perceived usefulness is limited to performance improvements in an organizational context, the characteristic relative advantage of the DOI can also encompass advantages that are not linked to the performance improvement of an individual and is not limited to the organizational context. According to the actual definition “(r)elative advantage is the degree to which an innovation is perceived as better than the idea it supersedes.” (Rogers, 1983, p. 213). As a consequence, when for example analysing the influence of environmental concerns on the adoption of EVs, several researchers frequently refer to the relative advantage an EV provides compared to ICCs regarding CO_2 emissions (Jansson, 2011; Schlüter and Weyer, 2019).

The characteristic of compatibility is used to analyse if an EV better corresponds with the values of a person and therefore leads to a higher adoption rate. The environmental benefit that an EV provides is again a good example for this characteristic. Theoretically, an EV should better correspond with the values of an environmentally aware individual than an ICC (Jansson, 2011).

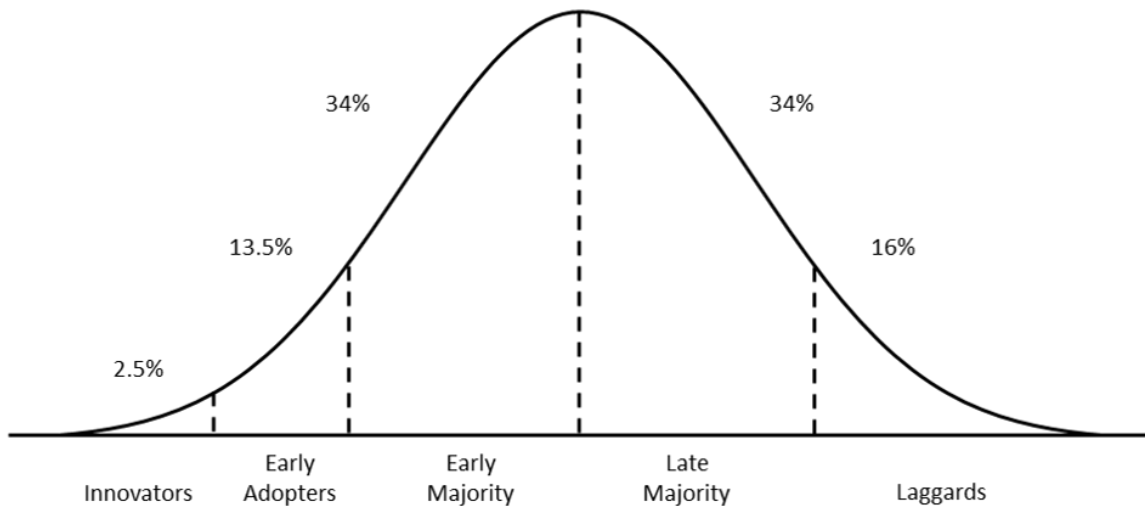
Observability can also be an important factor for the adoption of EVs. With an increasing number of new EV registrations people can better perceive the advantages of EVs. Advantages that can be noticed are for example the reduced noise from the motor (Graham-Rowe et al., 2012; Plötz et al., 2014) or subsidies that grant EV owners special permissions. Visible permission can for example take on the form of using bus lanes or dedicated parking spots for EVs. Furthermore, due to the high visibility of EVs people can better present their pro-environmental lifestyle or status Jansson (2011); Noel et al. (2019), which corresponds with the category of observability.

The influence of trialability on EV adoption has also been investigated in relation to EV adoption. Schlüter and Weyer (2019) for example has looked at the influence of EV car sharing on the adoption of EVs as this provides an opportunity to experience driving an EV before making a purchase decision.

Based on the factors discussed above, people form their attitude towards EVs and either purchase an EV or not. After using the EV for a certain time, the individual is either satisfied and continues driving it or switches back to an ICC or an alternative transportation mode.

Another important aspect of the DOI theory that has received widespread academic interest is its segmentation of the population based on when people adopt a new technology. According to the theory, a society can be classified into different groups that distinguish themselves based on the level of innovativeness, which is derived from how quickly they adopt the innovation. This is a relevant aspect as it is important to know what attributes early adopters embody that are different to later adopters. Rogers (2003) divided the society into five categories based on a time aspect when people acquire a new innovation. These categories are, in descending order based on their level of innovativeness, the Innovators, Early Adopters, Early Majority, Late Majority and Laggards. The groups of adopters with their corresponding approximated shares are also depicted in Figure 3.6.

Figure 3.6: Diffusion of Innovation Curve

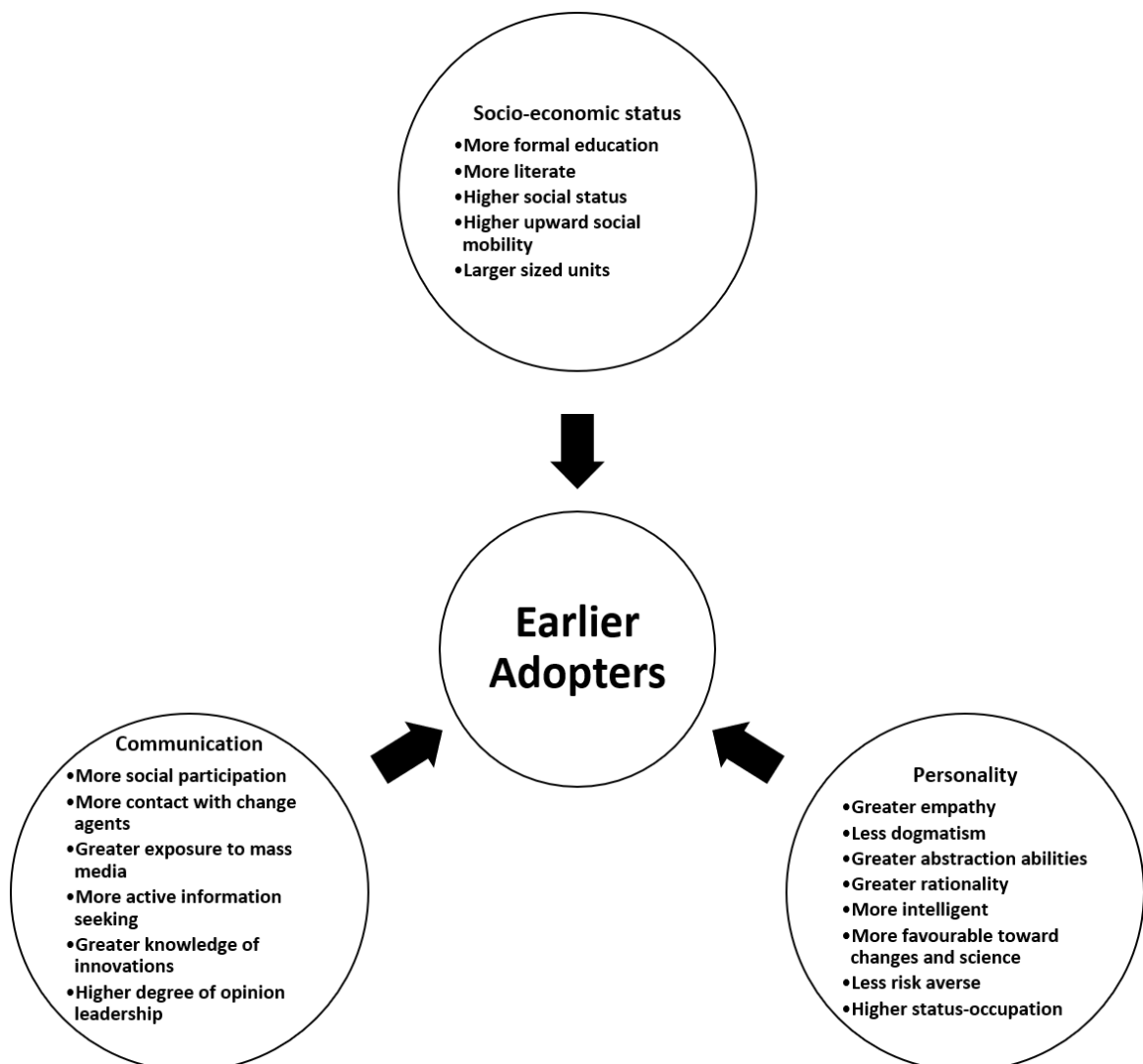


Note: Illustration by Rogers (2003)

It has been found that while the groups do not significantly differ in age, people that can be assigned to the groups of earlier adopters however differ based on other characteristics compared to the people who fall into the categories of

late adopters. According to Rogers (2003), past research thereby focuses on three groups of characteristics. These are socio-economic status, personality variables and communication behavior. In Figure 3.7, the categories and some important characteristics of earlier adopters are illustrated.² A few important differences are for example that earlier adopters often exhibit a higher level of education, a higher social status or engage in more social interactions. Furthermore, this group is considered to act more rational, open towards changes and less risk averse.

Figure 3.7: Characteristics of Earlier Adopters



Note: Own illustration based on the characteristics of earlier adopters discovered by Rogers (2003)

²A comprehensive list of differences can be seen in Rogers (2003).

The global stock of EVs accounted for approximately 1% in the year 2019 (International Energy Agency, 2020b). The technology is, therefore, still in its initial stages and the people who have bought an EV can according to Figure 3.6 be classified as Innovators. In terms of the EV market, it is important to understand the motivation of this group to adopt an EV as they are crucial to foster the market (Plötz et al., 2014). Based on the DOI the group of early adopters are important to make others aware and familiarise them with the innovation for example by openly communicating the advantages. This group for example takes on the highest risk, which in the EV market can be reflected by the less developed infrastructure, and lead with their behavior to the further development of the market. Consequently, multiple researchers have already investigated whether several characteristics of Innovators and Early Adopters described in Rogers (2003) also apply to the early adopters of EVs (e.g. Plötz et al., 2014).

3.2.1.4 Symbolic Motives and Self-identity

The last concept that should be mentioned as it is frequently employed by researchers (Graham-Rowe et al., 2012; Schuitema et al., 2013; Noppers et al., 2014; Rezvani et al., 2015) to explain the adoption of an EV is the concept of symbolic motives. In contrast to the theories previously discussed in this chapter, the concept of symbolic motives in this dissertation is not understood as one stand-alone theory but more as a collection of different theories that highlight the importance a product can have for an individual to express its identity. Rezvani et al. (2015) for example summarises the model of sign theory (Saussure, 1965), the self-image congruency theory (Sirgy, 1986), narratives of self theory (Giddens, 1991) and the costly signaling theory (Miller, 2009) under the concept of symbolic motives.

Pointed out by Giddens (1991) and Steg (2005), the purchase of a product is not only driven by practical and instrumental reasons but also by emotional rationales like the desire for self expression. A consumer can therefore use a product as a symbolic motive for the communication of his or her identity and signaling of status. In the context of the automobile market, the adoption of an EV can therefore be used by an individual to signal its pro-environmental behavior or interest in new innovations (Noppers et al., 2014).

Based on the costly signaling theory, the purchase of an EV might be particularly interesting for a customer who purchases such a vehicle type as a symbolic motive. This is because, an EV can be considered an expensive product and according to

the costly signaling theory the purchase of a product that entails higher financial and non-financial costs is capable of expressing the self-identity and status more strongly. Moreover, an EV is perfectly suitable to be a symbolic motive as it can easily be seen by many people (Griskevicius et al., 2010; Noel et al., 2019).

3.2.1.5 Concluding Remarks

The reviewed theories predominantly focus on explaining behavior or the adoption of an innovation on a micro-economic rather than a macro-economic level. Thus, they seek to explain and predict why an individual engages in a certain behavior. The focus on these theories can be explained by the research focus in this strand of literature. Previous research has predominantly investigated the driving factors of the EV market on an individual level. Since the EV market is not strongly developed most researchers also relied on the intention to adopt an EV rather than actual adoption behavior. To justify the selection of this approach and allow inferences from intention on actual adoption behavior, the researchers required a strong theoretical background.

Although, the theories discussed above are mostly used in micro-economic studies, they also contain macro-economic aspects and therefore can also be applied on a larger scale. The subjective norms dimension of the TPB for example reflects the pressure an individual receives from the society when engaging in a certain behavior. Thus, it can be interpreted as a macro-economic factor that influences the eventual behavior. The application of the DOI theory on a macro-economic level has already been proven by several researchers (Dickerson and Gentry, 1983; Kim et al., 2011). The diffusion of innovation curve that categorises a society into different levels of innovativeness is a good example for the macroeconomic application of this theory. Lastly, a society consists of individuals. Therefore, a shift of characteristics or attitude of a society can be traced back to a general shift of characteristics or personality traits of multiple individuals. Hence, theories that explain an individual's purchasing decision can also be expected to explain purchasing decisions on a macro-economic level.

Another observation that can be made in regard to the reviewed theories, is their similarity in some core points. This can partially be explained as some of them are based on the same theory. The TPB and TAM for example both are modifications of the TRA. Furthermore, all theories are developed to explain and predict human behavior, wherefore some overlap of the theories is not surprising.

3.2.2 Electric Vehicle Adoption

This section of the literature review is dedicated to providing an initial overview of the determinants applied to explain the adoption of EVs, investigated by previous research. It is by no means considered to be a comprehensive review and discussion of all studies published in this field of research. The focus rather lies on providing the reader with an idea of which factors can potentially influence EV adoption and have frequently been investigated. Furthermore, in this part of the literature review a phenomenon that often accompanies the application of survey methods in this strand of literature, which is known as the attitude-action gap, is described and potential downsides that arise from this phenomenon are discussed. Building on this gap, potential ways to circumvent the attitude-action gap are outlined. A more comprehensive review of EV adoption studies, that focuses on the specific gap this research tries to fill will be provided in chapter 3.3.

3.2.2.1 Determinants of the Electric Vehicle market

Previous literature has looked at a variety of determinants that could potentially explain movements in the EV market. Consequently, it is not surprising that good academic endeavours already exist that attempt to summarize the findings of previous research. A list of previous literature reviews is provided in Table 3.1. Due to the broad spectrum of research in this field, each review of the literature contributes to this field by focusing on specific sub-fields and gathering the knowledge obtained in these sub-fields. The reviews' focus can thereby range from a general review of EV adoption drivers such as in Coffman et al. (2017) or Kumar and Alok (2020) to reviews that focus on a specific determinant of EV adoption such as charging infrastructure (Funke et al., 2019) or incentives (Hardman, 2019). Furthermore, as the EV market has strongly evolved over the last years, it attracts more and more interest in this field of research, thus, providing the demand for new literature reviews that summarise the status quo in research.

The literature reviews on general EV adoption, inevitably already attempted to categorise the determinants of the market. Four of these categorisation approaches will now be briefly explained. As one of the pioneering literature reviews focusing on EV adoption research, Rezvani et al. (2015) are largely concerned with the factors that shape and explain an individual's attitude toward an EV. Thereby, the authors link the considered determinants to five theories that can explain and predict an

3.2. DRIVERS OF THE ELECTRIC VEHICLE MARKET

individual's adoption behavior. Thus, their review does not cover the full range of possible drivers of the market, but is limited to "... individual-specific psychological factors" (Liao et al., 2017, p. 253). Consequently, the categorization of Rezvani et al. (2015) does not seem appropriate for this research.

Table 3.1: Previous Literature Reviews

Source	Vehicle Type	Review Type	Review Focus
Al-Alawi and Bradley (2013)	EV (general)	Narrative	Market forecast
Rezvani et al. (2015)	EV (general)	Systematic	Drivers for and barriers against EV adoption
Coffman et al. (2017)	EV (general)	Systematic	Factors affecting EV adoption
Daina et al. (2017)	EV (general)	Systematic	Modelling EV use
Pettifor et al. (2017)	AFV	Systematic	Social influence on the AFV market
Liao et al. (2017)	BEV, PHEV	Systematic	Consumer preference
Hardman et al. (2017)	BEV	Systematic	Purchase incentives
Biresselioglu et al. (2018)	EV (general)	Systematic	Motivators and barriers for electric mobility in europe
Hardman et al. (2018)	BEV, PHEV	Systematic	Charging infrastructure
Jochem et al. (2018)	AFV	Narrative	Market forecast
Daramy-Williams et al. (2019)	BEV, PHEV	Systematic	User experience of PEVs
Funke et al. (2019)	BEV, PHEV	Systematic	Charging infrastructure
Hardman (2019)	BEV, PHEV	Systematic	Recurring and non-financial incentives
Lopez-Arboleda et al. (2019)	AFV	Systematic	Supply and demand side modelling of the transportation sector
Ayodele and Mustapa (2020)	EV (general)	Systematic	Life cycle cost analysis
Kumar and Alok (2020)	EV (general)	Systematic	Factors affecting EV adoption
Rajper and Albrecht (2020)	EV (general)	Systematic	Opportunities and barriers for EVs in developing countries

Note: Review type only distinguishes between systematic and narrative.

Another attempt to categorise the determinants of EV adoption has been carried out by Coffman et al. (2017). The authors initially broadly categorise the determinants into internal, external and policy mechanism that affect EV adoption. These categories are then refined by subcategories. For the group of internal factors, the subcategories vehicle ownership costs and driving range are created. External factors include fuel price, consumer characteristics, charging networks and public visibility as well as social norms. Policy mechanism can be split up into financial and non-financial incentives, supporting charging infrastructure and awareness raising policies.

A recently published literature review has been executed by Kumar and Alok (2020). The authors distinguish between five categories of variables that have been investigated literature focusing on EV adoption. These are antecedents, mediators, moderators, consequences and socio-demographic variables. The variable group of consequences, however, does not represent drivers of the market but form the category that is influenced by the drivers. Thus, only the other four categories are of interest for this study. As Kumar and Alok's (2020) categorization is based on a relationship map of EV adoption, next to the antecedents of the market, the authors further distinguish between moderating, mediating and socio-economic variables. This is because these groups of variables might exhibit an influence on EV adoption at different stages in the purchasing process. While according to Kumar and Alok (2020) antecedents and socio-demographic variables shape consumer adoption intention and therefore indirectly influence the actual adoption of EVs, moderating variables can either amplify or lessen an individual's attitude towards an EV. In their study, Kumar and Alok (2020) pointed out that the majority of research focuses on intention to adopt an EV rather than actual adoption behavior. Although, the authors state that they make an explicit distinction between those cases when discussing the literature, the focus of previous studies nevertheless could strongly influence the categorisation applied in their study.

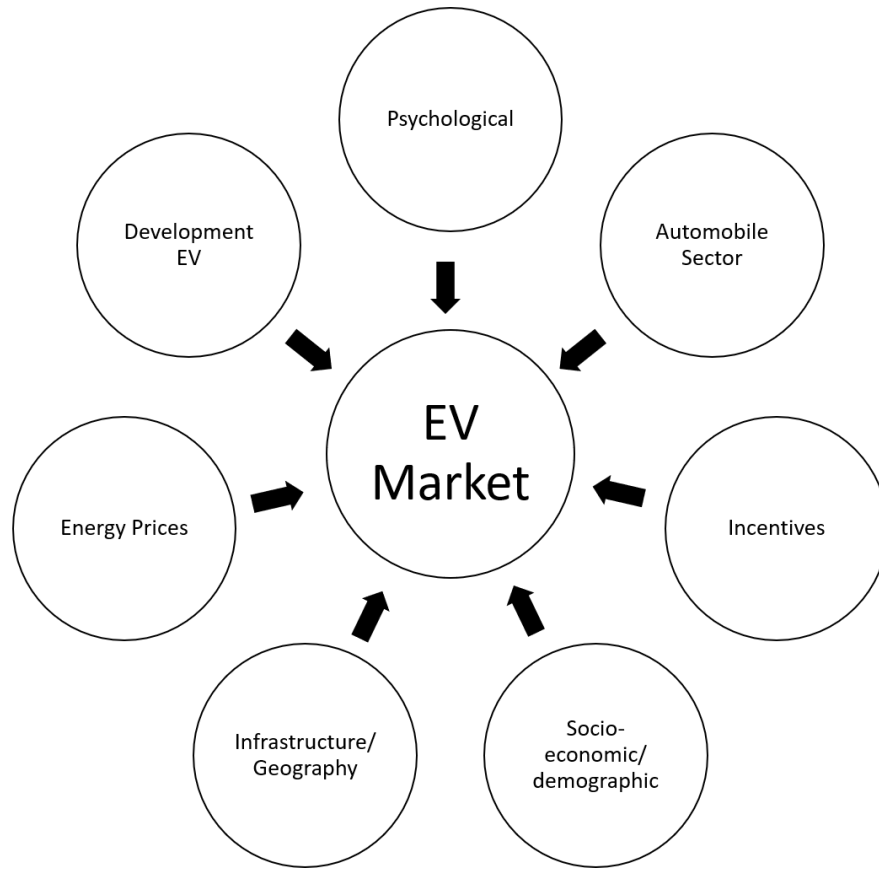
The last review that will be presented in this context was executed by Liao et al. (2017) and focuses on consumer preferences for EVs. Thus, only studies were investigated in this review that rely on stated preference data. In their study, the authors establish a conceptual framework for the adoption of EVs based on the reviewed literature. The framework describes two categories of determinants that can explain the utility an individual receives from the adoption of an EV and therefore explains the adoption motivation. These groups are labeled individual-related variables and attributes which are further split up into subcategories. The individual-related variables consists of (1) socio-economic characteristics, (2) psychological factors, (3) spatial factors, (4) mobility and car-related conditions, (5) experience with EV and (6) social influence. The category attributes focuses on the characteristics of the vehicle type and includes (1) financial attributes, (2) technical attributes, (3) infrastructure attributes and (4) policy attributes.

As discussed above, there are different ways to categorise the determinants of the EV market and each has its own merits. All categorisations discussed above, except the one of Rezvani et al. (2015), are extremely detailed and split the

variables into rather specific subcategories. Minor deviations in the categories exist which can potentially be explained by differences in the objectives of the reviews or different study samples. For example while Liao et al. (2017) only consider consumer preference studies in their review and thus only include studies that rely on stated preferences, Kumar and Alok (2020) did not differentiate based on the methodology of the considered studies. Furthermore, categorisations are subjective and should be aligned to the purpose of the review and its specific focus. The categorizations described above likely intend to provide a detailed and comprehensive summary of variables that have been investigated. While this is useful in the context of a comprehensive literature review the level of detail may be seen as cumbersome when trying to provide a general overview of investigated areas. Since the purpose of this section is to provide the reader with an idea of which determinants have been investigated and does not aim to provide a comprehensive review, a broader categorisation of the variables will be used to facilitate the classification of variables.

In this research the determinants will be categorised into seven different groups, which are depicted in Figure 3.8. In particular, these determinants relate to the automobile sector, incentives imposed by politics, socio-economic/-demographic factors, infrastructure & geography, energy prices, the technological development of EVs, as well as psychological factors. A more detailed description of the categories will take place in the following sub-chapters.

Figure 3.8: Determinants of the EV Market



3.2.2.1.1 Automobile Sector

The first group of this categorisation includes determinants dealing with the automobile sector. Thereby, variables that explain characteristics or developments of this sector as a whole or an entity situated in this sector can be assigned to this group. In this research the automobile sector does not only refer to the niche market of EVs but also includes the ICC sector. Determinants representing the automobile sector are often included as control variables into analyses. Controlling for the vehicle stock or the number of new registrations in a cross region or time series analysis for example can help account for a generally stronger or weaker automobile market in a country or year (Heidrich et al., 2017; Wang et al., 2019).

As previously mentioned, this category does not only contain determinants that represent the automobile sector as a whole but also includes factors on lower levels such as car manufacturers or dealerships. For example the unavailability of EVs at car dealerships or the relatively long delivery time for such a vehicle, which have

proven to be barriers for the adoption of EVs (Matthews et al., 2017; Cahill et al., 2014), can also be assigned to the group automobile sector. The reason for including variables of entities in the automobile sector in this category is that they allow inferences on the sector as a whole.

3.2.2.1.2 Incentives

Incentives are issued by the state and are therefore a policy mechanism that seeks to promote the adoption of EVs. This category can broadly be divided into financial and non-financial incentives. Financial incentives are monetary grants or benefits an individual receives when purchasing an EV. These financial benefits can take on different forms such as direct grants for the purchase at the point of sales or reoccurring subsidies such as the exemption or reduction of annual taxes (e.g. Münzel et al., 2019; Sierzechula et al., 2014) Financial incentives in the EV market do not only apply to the vehicle itself but can also be granted to equipment for this product. Several countries for example support the installation of charging stations in private homes financially and try to foster the development of this market through this measure. The influence of such an incentive has also been the subject of various research (Narassimhan and Johnson, 2018; Wee et al., 2018).

Non-financial incentives are special permissions a country, city or region grants to EV drivers but not to drivers of ICCs. One of the most commonly applied non-financial benefits is access to bus lanes or high occupancy vehicle (HOV) lanes. Employing these grants, governments improve the convenience of driving EVs which is especially beneficial in regions with high traffic. Another example for a non-monetary benefit EV drivers obtain in several countries, are parking spots exclusively provided for EVs. The results obtained in the stream of research focusing on the influence of incentives are mixed (Coffman et al., 2017; Münzel et al., 2019). For both financial and non-financial incentives research exists that provides evidence for a significant positive impact of incentives on EV adoption (Sierzechula et al., 2014; Vergis and Chen, 2015; Rietmann and Lieven, 2019). A more detailed discussion about the extant literature focusing on incentives will take in chapter 3.5.

3.2.2.1.3 Socio-economic/demographic

The effect of socio-economic and -demographic variables has frequently been analysed to cluster the population into segments and thus to identify characteristics of

individuals that are more likely to engage in a purchasing behavior. A few of the most frequently individual related determinants were summarised by Kumar and Alok (2020) and are for example: age (Plötz et al., 2014; Nayum et al., 2016; Sovacool et al., 2018), education level (Plötz et al., 2014; Nayum et al., 2016; Sovacool et al., 2018), income (Axsen et al., 2016; Nayum et al., 2016; Morton et al., 2017), gender (Plötz et al., 2014; Sovacool et al., 2018), household size (Liu et al., 2017; Morton et al., 2017) or commuting mode (Liu et al., 2017; Morton et al., 2017).

The significance of these variables, however, strongly differs based on the region that is investigated. A potential explanation for this outcome could be differences in culture or other country specific conditions (Kumar and Alok, 2020).

An observation that can be made is that studies that rely on surveys as a data collection method more frequently focus on the effect of socio-economic and -demographic variables than studies that have used actual sales data and analyse the relationship on a macroeconomic level. A potential explanation for this is that these factors are often automatically included in a survey based analysis to describe the sample and control for potential sampling errors (Gesis Leibniz Institute for the Social Sciences, nd). Studies that use market data in this stream of literature often use socio-economic determinants as control variables to account for differing living conditions (Münzel et al., 2019).

3.2.2.1.4 Infrastructure/Geography

The fourth category of determinants in this categorisation system encompasses all factors that focus on the infrastructure for EVs and all geographical aspects that could foster or hinder the adoption of an EV. The reason to merge these two aspects into one category is that some factors strongly correlate with each other and can therefore be allocated to both categories which makes these two closely interlinked.

One of the most researched determinants in this regard is the charging infrastructure. Although, the causality between EV adoption and the number of charging stations is not definitively answered (Liao et al., 2017; Münzel et al., 2019; Li et al., 2017; Serradilla et al., 2017), several researchers conclude that the charging infrastructure is an important factor for EV adoption (e.g. Bakker et al., 2014; Berkeley et al., 2018). Thereby, it is important to mention that there are indications that not only the quantity of charging stations are important for the development of the market but also the location where they are positioned (Lieven, 2015; Melliger et al., 2018) and whether they are fast or normal chargers (Neaimeh et al., 2017; Bunsen

et al., 2018). This example also highlights the connection between infrastructural and geographical aspects. Other examples for determinants that can be assigned to this category are the level of urbanity, miles roadway or proximity to a major city.

3.2.2.1.5 Energy Prices

The category energy prices does not only include the prices for electricity, which represents the fuel for EVs, but also the prices of traditional fossil fuels such as gasoline or diesel. While electricity prices are expenses that accrue directly when the EV is operated, the prices of fossil fuels represent costs that an individual saves when switching to an EV. Thus, these determinants have no influence on the costs of acquisition but play a significant role for the operational costs and therefore the cost-effectiveness of the vehicle type. Consequently, energy prices are often a key issue for research focusing on the total cost of ownership (TCO) of EVs (Coffman et al., 2017; Bubeck et al., 2016; Lévy et al., 2017).

In the stream of literature focusing on EV adoption, when considering energy prices, previous research has either accounted for one of the prices (fossil fuel (Jenn et al., 2013; Qiu et al., 2019), electricity (Clinton and Steinberg, 2019)) or both prices (Vergis and Chen, 2015; Münzel et al., 2019). When including both prices into the investigation, a few researchers have decided to use a ratio of electricity and fossil fuel prices, as this value essentially represents the operational savings of EVs (Münzel et al., 2019).

3.2.2.1.6 Electric Vehicle Development

This category summarises all factors that focus on the vehicle type itself. It can be considered as a part of the automobile sector, however, due to the importance of these factors they form an own group in this categorisation system. The determinants that can be assigned to this group strongly correlate with the subcategory technical attributes of Liao et al. (2017) and thus also include factors that are concerned with the battery, performance or emissions of EVs.

As range anxiety has been found to be one of the greatest barriers for adopting an EV (Liao et al., 2017), several researchers have focused on the driving range aspect of an EV (Melliger et al., 2018; Skippon et al., 2016). Since the driving range of an EV strongly depends on the installed battery, researchers have ultimately investigated the importance of this vehicle attribute. Thereby, most researchers have found a positive influence stemming from a longer driving range on the

adoption of EVs (Liao et al., 2017). Another example of a factor that has witnessed significant academic interest and can ultimately be traced back to the development of the batteries is the recharging time of such. Since an EV requires a considerable amount of time for a complete recharge, it can pose a severe market barrier. Thus it is not surprising that the results of several researchers indicate a negative relationship between charging time and EV adoption behavior (Graham-Rowe et al., 2012; Hackbarth and Madlener, 2013).

Another important attribute of an EV that at this point should be highlighted is the reduced emissions of EVs compared to ICCs. As mentioned in the introduction, one reason why EVs have received increasing interest over the last years is their ability to not emit any CO_2 when they are operated and therefore contribute to the endeavours to stop climate change. However, as a large share of the electricity that is used to power the engine is not generated by sustainable energy sources (Hackbarth and Madlener, 2013) and the production and maintenance still rely on processes that emit CO_2 , some researchers try to assess the influence of an EVs CO_2 balance on its adoption. The results indicate that while the improved CO_2 balance of an EV could be beneficial to foster the adoption of EVs, the outcomes of the study clearly suggest that the improvement of other car attributes such as driving range is, however, of higher importance for potential customers (Hidrue et al., 2011; Graham-Rowe et al., 2012).

The category development EV is in this research, however, not limited to technological attributes of an EV but also includes general factors such as vehicle ownership costs or the number of available EV models.

3.2.2.1.7 Psychological

The last category that can be determined based on previous studies, deals with the beliefs and personality traits of people regarding EV market influencing aspects and are summarised as psychological determinants. Psychological determinants also include factors that for example provide insights regarding an individual's perceptions, attitudes, norms or moral values. Liao et al.'s (2017) category of factors from psychological theories, therefore, most closely resembles the understanding of psychological factors applied in this study.

Thus, this category includes factors such as environmental concerns, innovativeness, symbolic motives, perceived risks or emotions. Psychological factors are by many researchers considered to be important determinants as they have been found

to significantly influence an individual's intention to adopt an EV (e.g. Nayum et al., 2016; Kumar and Alok, 2020; Liao et al., 2017; He et al., 2018). The reason why an individual might purchase an EV instead of an ICC is for example to express its identity and therefore an EV can be considered as a symbolic motive. Researchers in this stream of literature have also found that people aim to improve or secure their social status when purchasing an EV (Helveston et al., 2015; Qian and Yin, 2017). Thus an EV can for example also be considered a status symbol.

In Chapter 3.4 a more detailed discussion on psychological factors will take place. Thereby, a focus will be laid on environmental concerns and innovativeness.

3.2.2.1.8 Concluding Remarks

As shown in the beginning of this sub-chapter a few academic endeavours to categorise the drivers of the EV market already exist. These categorisations are extremely comprehensive and provide detailed insights into the status quo of research, but in turn entail a large degree of complexity. This can be considered as cumbersome when the aim is to provide the reader with an initial understanding of potential influencing factors of the market and not reviewing the entire literature in this stream of research. Consequently, a new and more simplified categorisation of determinants, which can be seen in Figure 3.8, was introduced in this sub-chapter. This categorisation should, nevertheless, be able to capture each determinant in one of the categories.

One important point that should be raised at this stage is that most research in this strand of literature focuses on determinants and their influence on intention to adopt an EV rather than actual adoption behavior (Coffman et al., 2017; Kumar and Alok, 2020). Thus, it can be assumed that the categorisation systems applied in previous literature reviews might be strongly influenced by these studies. Previous research in this stream of research, however, has uncovered that an individual's intention does not necessarily correspond with its eventual behavior. This situation is also referred to as the *attitude-action gap* and will be discussed in more detail in the following section.

3.2.2.2 Attitude-Action Gap

The attitude action gap refers to the situation when an individual's actions diverge from its intentions or stated preferences (Coffman et al., 2017). This occurrence can partially be explained with some of the theories discussed in the previous chapters.

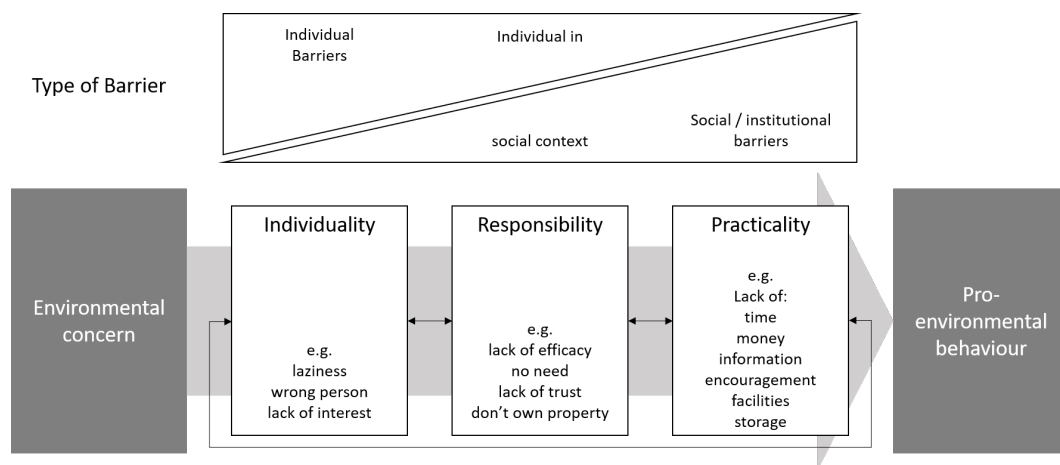
When looking at the TPB for example, it can be seen that not only the behavioral intention but also the perceived behavioral control dimension affects the eventual behavior. Thus, certain barriers might lead to the situation that people forgo the adoption of the behavior or product, although the individual exhibits a positive attitude towards it.

Researchers have found that this phenomenon can often be observed in environmental related topics (Farjam et al., 2019). A simple explanation for the occurrence of this phenomenon is that alternative goals or behaviors are favored and therefore environmental supporting actions become of secondary importance (Stern, 2000; Rezvani et al., 2015). Several different attempts have been undertaken in academic research to provide a detailed explanation or model for the causes of the occurrence of an attitude-action gap in an environmental context. However, according to Kollmuss and Agyeman (2002), none of the developed models are capable of capturing all factors that can potentially explain this gap. Furthermore, the authors claim that a model that would incorporate all factors might be too complex and therefore lose its practicality. Nevertheless, various models have been established that demonstrate how other critical factors might play a role in the dissonance between intentions and behaviors when it comes to pro-environmental behavior. One exemplary model that will briefly be discussed at this point is that of Blake (1999). This is because his model in contrast to other models that aim to explain predictors of pro-environmental behavior, such as the TPB, takes into account structural and institutional constraints. Furthermore, it does not presume that people make rational choices (Blake, 1999; Kollmuss and Agyeman, 2002). In his model Blake (1999) identifies several barriers that might explain why people's environmental concerns do not lead to pro-environmental behavior. These can be divided into three groups and are depicted in Figure 3.9.

The first group of factors that the researcher identified are individual barriers and are concerned with a person's attitude. This category poses a barrier, especially for individuals with a low level of environmental concerns. When environmental concerns are conflicting with other attitudes, which are prioritised by the individual, he or she will not engage in the pro-environmental behavior. The second group of barriers is termed responsibility and entails factors that influence environmental behavior externally. Even though people might have concerns about the environment, they do not feel responsible as an individual to act in a more environmental friendly manner. The reason for this could be that an individual

considers its own measures as not sufficient to make a difference. Furthermore, people might feel that other individuals or groups, which they consider to be more influential, are obliged to act environmental friendly as they consider them to be more effective (Blake, 1999; Kollmuss and Agyeman, 2002). The last set of barriers, according to Blake (1999), are practicality related issues and should reflect social and institutional constraints. Although, someone might have a positive attitude or an intention to adopt a pro-environmental behavior, these barriers can nevertheless hinder the adoption of such. A practical constraint is for example the lack of financial means for the acquisition. When people cannot afford the price of an environmental friendly product, they are excluded from its usage (Blake, 1999; Kollmuss and Agyeman, 2002).

Figure 3.9: Barriers between Environmental Concern and Action (Blake, 1999)



Note: Illustration by Kollmuss and Agyeman (2002)

As previously mentioned, no model provides a perfect comprehensive explanation of the attitude-action gap. The model of Blake (1999) is also not exempt of certain limitations. According to Kollmuss and Agyeman (2002), this model includes external as well as internal factors and combines them, however, lacks to account for the influence of social factors. The authors point out that the model cannot explain the influence of for example familial pressure.

Research in this stream did not only attempt to investigate the attitude-action gap on a theoretical basis but also provides empirical evidence applying different methodologies. In an early study, Diekmann (1992), using a low-cost high-cost model, for example found that people's pro-environmental actions diminish when the costs of the behavior increases. Costs in this context must not be interpreted

in a pure economic sense but can also be seen as for example time requirements to engage in a pro-environmental action. These findings have been supported by later studies (Diekmann and Preisendörfer, 2003; Farjam et al., 2019). Farjam et al. (2019) for example applied an experimental model and tested the effect of pro-environmental attitudes on actual behavior under different conditions. Participants of the experiment were given the choice between monetary gains or a donation that offsets carbon emissions. For the purpose of the experiment, each candidate received an endowment of an experimental currency. Shares of this currency could either be used for a donation or saved in the endowment. At the end of the experiment, the participant received the difference between the starting value of the endowment and the donations as a payoff. To test for the low-cost hypothesis, the researchers have altered the exchange rate of the experimental currency. In accordance with the low-cost hypothesis, Farjam et al. (2019) have found that people in the group with a higher conversion rate are less willing to allocate money to a pro-environmental action. This is because this group faces higher opportunity costs in form of forgoing monetary gains. Another interesting study in this regard has been carried out by Babutsidze and Chai (2018). The researchers have found that people are more inclined to imitate *green* behavior of their social environment if it is visible to others. Hence, from the results of the study it can be derived that the attitude-action gap might be less severe for visible green behavior. An interesting review of extant literature focusing on the attitude-action gap in environmental behavior has been executed by ElHaffar et al. (2020).

These studies should highlight the interest and importance of the attitude-action gap in this stream of literature. Furthermore, it emphasises that in some cases it is not sufficient to analyse the intention of individuals and then draw conclusions on actual adoption behavior.

Considering the specific case of EV adoption, some of the general findings in the field of pro-environmental behavior already suggest the existence of an attitude-action gap in this market. In particular, according to the low-cost hypothesis the adoption of an EV might be hindered due to the relatively high purchasing prices of EVs. Looking at previous literature, the attitude-action gap in the EV market has already been confirmed by several scholars (Lane and Potter, 2007; Mairesse et al., 2012; Shepherd et al., 2012; Aksen et al., 2009; Brownstone et al., 2000). Lane and Potter (2007), in their study for example make use of two independent studies to investigate the existence of an attitude-action gap for cleaner vehicles in

the UK. While the first study, conducted by Ecolane Transport Consultancy, focuses on the attitudes of potential consumers towards environmental friendlier cars, the second study, which was carried out by the Open University's Design Innovation group, has investigated "hotspot" factors that influence the adoption of low carbon cars. The authors, conclude that although consumers are in general concerned about the environment, these concerns have no or just a subordinate influence on the purchase of a low carbon vehicle. In addition, the researchers have found that the knowledge about car attributes in relation to the vehicle's environmental impact is extremely low, supporting further the existence of an attitude-action gap. Another study that has analysed the presence of the attitude-action gap in the EV market, was performed by Mairesse et al. (2012). In two interview groups, the researchers in total surveyed 74 volunteers regarding the probability of purchasing car models that differ based on attributes such as purchasing price, life-cycle costs or environmental performance. The results indicate that although environmental performance plays a role in the interviewees decision, a higher importance is often assigned to the other attributes making these more decisive factors in the EV purchasing decision. The results of the analysis are similar to the results of Lane and Potter (2007) and indicate that other car attributes are more important than the environmental performance, supporting the existence of an attitude-action gap in this market.

A study that has not specifically mentioned the attitude-action gap, however provides evidence of its existence was executed by de Rubens (2019). The researcher carried out a comprehensive survey in five different Nordic regions with the objective of determining different customer groups and investigating customers' interest in purchasing EVs. After clustering the respondents into six different customer groups, the scholar found that although the group with the highest EA level has the largest interest in EVs, this group exhibits the second smallest ownership ratio of EVs. Even the customer group this study refers to as 'Sceptics' (a cluster of people that scored low on EA) demonstrates a more than four times higher EV ownership ratio.

Methodologically, another approach researchers have frequently used to determine the existence of an attitude-action gap was by comparing the outcomes of stated preference to revealed preference analyses (Brownstone et al., 2000; Axsen et al., 2009). In stated preference surveys, respondents are normally given different options from which they have to select the one they consider the best. Based on

the answer, researchers can derive which attributes or combination of attributes provide the greatest utility. In context of the car market, the survey setting is often constructed in the way that the researcher provides the survey respondent with alternatives that distinguish themselves from each other in regard to certain car attributes. Revealed preference data on the other hand, is data derived from actual behavior and assumed to be more representative of consumer preferences (Coffman et al., 2017). A study setting that relies on revealed preference data to analyse the car market, can for example use the number of sold cars of a model and compare its attributes to other car models and their corresponding sales numbers. Based on the difference in the sales, the utility certain car attributes provide to customers can be derived. The disadvantage of revealed preference data is, however, that explanatory variables often strongly correlate, limiting the applicability of this method (Kroes and Sheldon, 1988; Axsen et al., 2009).

Studies, applying both stated and revealed preference data have found that forecasts relying on stated preference data strongly overestimate EV and HEV uptake (Brownstone et al., 2000; Axsen et al., 2009). This further confirms the existence of an attitude-action gap in the EV market. Thus the question arises, how the attitude-action gap can be circumvented and research on actual EV adoption can be conducted.

3.2.2.3 Measuring Electric Vehicle Adoption

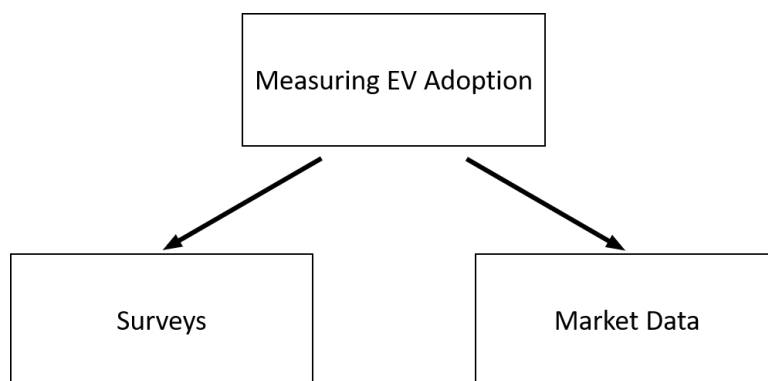
Due to the attitude-action gap, there are only two ways to obtain data, that can be used to draw conclusions on actual EV adoption. These methods are either by surveying EV owners or using market data (Li et al., 2019; Coffman et al., 2017). The former method, however, can be exposed to certain limitations that can potentially compromise the reliability of the results (Smith et al., 2017). One such limitation is biases. Biases such as leading or social desirability bias can significantly influence the answers of respondents and therefore potentially compromise the reliability of a study (Smith et al., 2017; Hafner et al., 2017). When investigating social desirability in regard to environmental topics, studies have for example found a strong tendency of survey respondents to over-report environmentally responsible actions and their willingness to pay (Krumpal, 2013; Kovalsky and Lusk, 2013). This might raise general concerns about the significance of the impact of determinants on the EV market and highlights the necessity to investigate actual sales data (Moser, 2015).

Evidence for the potential issue of a leading bias, when applying a quantitative survey approach to analyse the determinants of car purchases has been uncovered by Hafner et al. (2017). Carrying out qualitative surveys with participants that have recently bought a car, the researchers have found that the answers differ from the attributes quantitative studies often found to be important. The authors of the study hypothesise that the reason for this could be traced back to the nature of the questions asked in quantitative surveys. Survey participants may have assigned higher importance to a car attribute that they would spontaneously not have thought about, had it not been explicitly addressed in the study. For instance, the researchers have found that, while in quantitative surveys environmental factors have often been identified to be crucial factors for the selection of a car, this car attribute was only rarely mentioned in the qualitative survey they conducted. In contrast, image related factors were found to be far more decisive in their study compared to quantitative studies.

Furthermore, surveys depend on a high response rate, wherefore it is either difficult to generate a sufficient sample size that is large enough to be representative or often only possible with extensive costs and effort. This is especially the case when investigating a large geographic region. This effect can also be perceived when looking at previous studies. Most studies either focus on a single country or relatively small regions.

Another observation which can be traced back to the data collection method of surveys is the lack of studies investigating the development over time (Kumar and Alok, 2020). As most studies only consider data that was collected at one point in time, insufficient conclusions can be derived about the development of potential determinants on the motivation to purchase an EV.

Figure 3.10: Measuring EV Adoption



3.3 A Systematic Literature Review of Electric Vehicle Adoption Studies

Based on the findings in the previous sections, a lack of research focusing on actual EV adoption can be identified. In addition, the importance to execute studies on EV adoption due to significant differences between intention and adoption behavior, has been elaborated. Furthermore, potential biases and limitations of studies using surveys as a data collection method to obtain EV adoption information have been highlighted. Consequently, in this section of the literature review, studies focusing on EV adoption by applying econometric approaches on actual market data will be reviewed. To obtain a comprehensive overview of the state of research in this strand of literature, a systematic literature review (SLR) is applied. The decision to incorporate an SLR instead of a narrative review is based on the advantages this method entails, provided that an agreed terminology in this strand of literature exists, as is the case in the EV market. Petticrew and Roberts (2005), Tranfield et al. (2003) and Mallett et al. (2012) point out that a systematic review is a more transparent and thorough alternative compared to narrative reviews. The transparency of this review style is ensured with a detailed description of the search process. This will also provide other researchers the ability to replicate the study. An SLR is also considered to be more thorough as it increases the probability that each study, suitable for the predefined research question will be reviewed. In addition, the authors claim that an SLR minimizes the influence of an implicit research bias and due to the comprehensiveness that goes along with this review type, researchers are more capable to obtain a full picture of the status quo in a stream of literature.

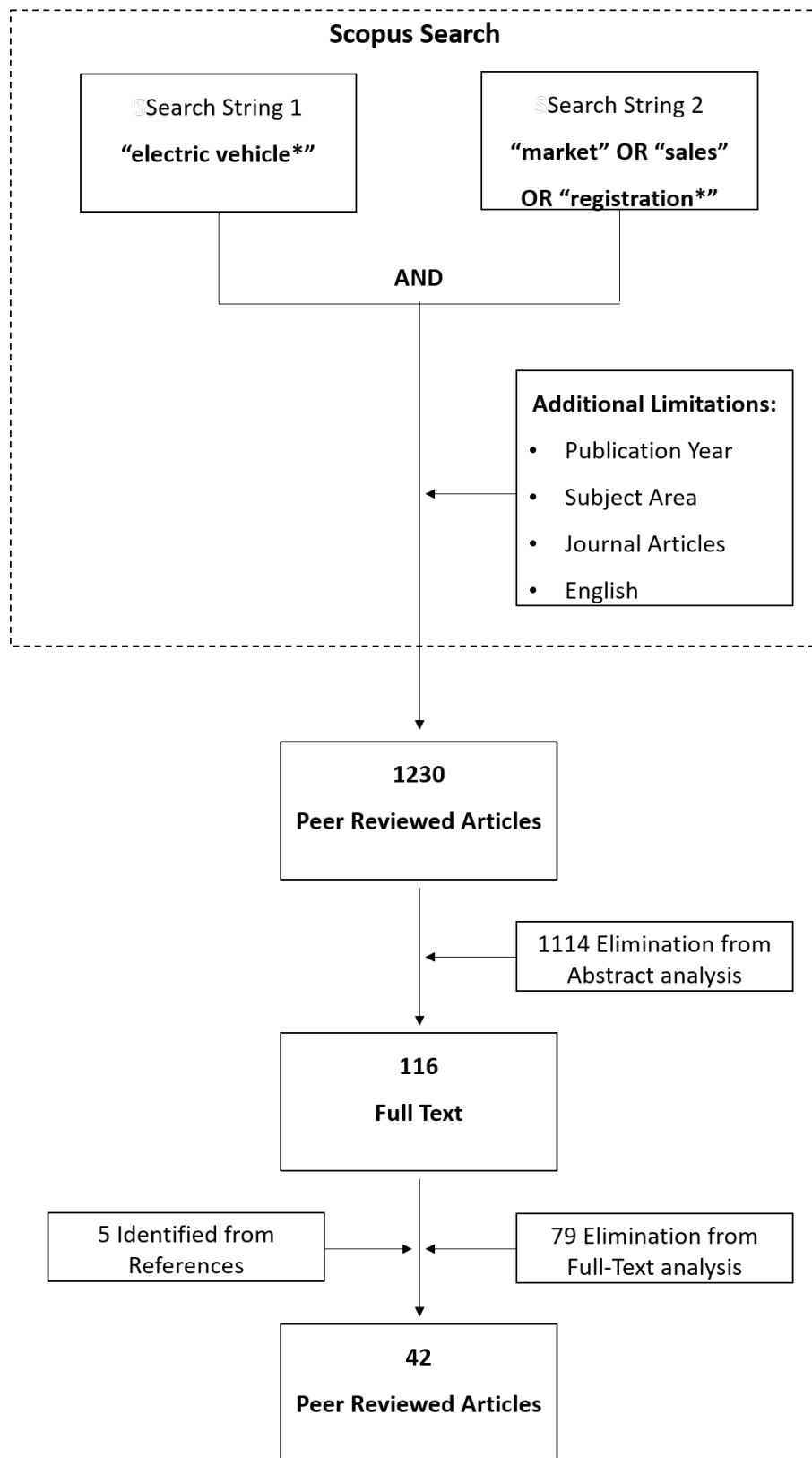
In the following, the selection of the sample will be explained in detail. Thereafter, a discussion of the identified literature with an emphasis on the applied statistical approaches and the investigated variables takes place. A summary of the key findings and recommendations for future research will also be provided.

3.3.1 Sample Identification

For the search, one of the biggest literature data banks, Scopus was utilized. An illustration of the review process can be seen in Figure 3.11.

3.3. A SYSTEMATIC LITERATURE REVIEW OF ELECTRIC VEHICLE ADOPTION STUDIES

Figure 3.11: Sample Identification



The search code applied in this study comprises two search strings and is as follows:

“electric vehicle*”
AND
“market” OR “sales” OR “registration*”

The selection of rather broad search terms was intentional, to reduce the probability of excluding relevant studies. Incorporating electric vehicle as the first search string, covers all vehicles that are to some degree driven by electricity. This entails hybrid electric vehicles, plug-in hybrid electric vehicles and battery electric vehicles. Although, this research has previously defined EVs to only consist of PHEVs and BEVs, literature investigating determinants for the adoption of HEVs will also be reviewed in this subchapter. The inclusion of these studies in this SLR has several reasons. First of all, a few studies exist that have aggregated data for BEVs, PHEVs and HEVs (Chen et al., 2015; Guo et al., 2020). Excluding these studies would result in an incomplete overview of the status quo in research. Furthermore, including studies that have focused on EVs allows to point out potential differences and similarities of the determinants that drive the adoption of these vehicle types. In addition, a potential research focus development can be assessed. Lastly, HEVs also incorporate some vehicle attributes of PHEVs and BEVs. An analysis based on the determinants of the HEV market can therefore allow inferences on the PHEV and BEV market. Thus the term EV in this specific section of the analysis refers to the vehicle types HEVs, PHEVs and BEVs.

As the focus of this SLR is to analyse literature that has employed actual sales/market data, relevant literature can most likely be identified with the search terms in the second search string. However, in case of different terminology the references of the selected papers were checked for potential literature not covered by the search code. In this study only peer reviewed articles are considered to ensure that the quality of the articles comply with a certain standard. Furthermore, the subject areas were limited to environmental sciences, social sciences, business, management, accounting, economics, econometrics and finance to filter out more technology and engineering related papers. In line with previous literature (Kumar and Alok, 2020) only studies starting from 2010 are considered. This is because at this time EVs initially entered the mainstream market. In addition, it more accurately reflects the current status of research as the EV market has rapidly changed

over the last years (Kumar and Alok, 2020). The search was executed on the 30th June 2020 and eventually yielded a total of 1,230 papers. In the following step the abstracts of these articles were screened for eligibility. As pointed out earlier, this literature review focuses on studies that have used sales data to statistically analyse the influence of factors on the EV market. Hence, a pre-selection of papers that do not fulfil this requirement could be made and consequently eliminated. Papers that were eliminated for example focused on vehicle types other than passenger cars or the influence of EVs on GHG emissions, rare earths or renewable energy production. Papers that try to forecast the EV market were also excluded from the analysis as these studies do not correspond with the focus of this research.³ Furthermore, papers that do not apply an empirical approach were also excluded from the analysis. In the process of the abstract analyses 1,114 papers were eliminated. For the remaining 116 papers the full text was obtained and analysed. Of these, 79 articles were excluded from the study, leaving 37 peer reviewed publications from the SLR. These publications were screened for references from which 5 additional articles eligible for inclusion were identified. Finally, the sample for this review consists of 42 publications.

3.3.2 Results

In total, 42 peer reviewed articles that fit into the scope of analysis were identified based on the SLR. A list of all articles with the corresponding titles is depicted in Table 3.2. To provide further information about the studies, columns containing information about vehicle type, geographic area and time resolution that was under investigation and the applied statistical method have been added to the table.

As it can be seen from the titles of the articles, studies have focused on a variety of possible determinants of the EV market. These range from charging infrastructure to air pollution level of a city. The category of determinants that has, however, received the most attention in academic research are subsidies or incentives. This can possibly be explained by the multifaceted nature of the way incentives can be applied. Furthermore, states and cities can directly control incentives which hypothetically make them simple control elements to influence EV adoption. A further discussion of these variables takes place in the subsequent chapter.

³A comprehensive SLR of forecast studies can be found in Jochem et al. (2018).

Another more general observation derived from the table is that earlier studies have predominantly focused on the HEV vehicle type. An explanation for this would be that this technology was introduced to the mainstream market earlier, wherefore more observations are available. With the availability of more data, subsequent studies have altered their focus from HEVs to PHEVs and BEVs.

When analysing the identified literature with regard to its geographic scope, different levels of dispersion can be seen. The analyses range from cross-country studies including more than 30 countries to lower-tier analyses within a single city. Thereby, the decision of the geographic scope can have a significant influence on the variables and the applied statistical model. While for example cross country analyses can only consider nation-wide subsidies, a study that focuses on EV market differences within a country is limited to subsidies of states or cities. Another aspect to consider is, in case census tract data is available, a more accurate analyses of socio-demographical factors can be made on lower-tier level as it provides a higher level of data accuracy. Derived from the table, it can also be concluded that most studies have analysed regions where the EV market has already been more strongly developed such as China, US or the Nordic regions.

In the following sub-chapters a more detailed analysis of the applied statistical models and the investigated variables will take place.

Table 3.2: Identified Literature

Author	Title	Vehicle Type	Geographic Region	Time Resolution	Method
Chandra et al. (2010)	Green drivers or free riders? An analysis of tax rebates for hybrid vehicles	HEV	Canadian provinces	1989-2006, yearly	FE panel data reg.
Gallagher and Muehlegger (2011)	Giving green to get green? Incentives and consumer adoption of hybrid vehicle technology	HEV	US states	2000-2006, quarterly	FE panel data reg.
Jenn et al. (2013)	The impact of federal incentives on the adoption of hybrid electric vehicles in the United States	HEV	US national data	2000-2010, monthly	FE panel data reg. / GMM with LDV
Saarenpää et al. (2013)	Geodemographic analysis and estimation of early plug-in hybrid electric vehicle adoption	HEV	Finland, census tracts	2010/2011	K-means cluster with correlation analysis
Sierzechula et al. (2014)	The influence of financial incentives and other socio-economic factors on electric vehicle adoption	PEV	Global countries	2012, yearly	Cross sectional OLS
Wesseling et al. (2015)	Business Strategies of Incumbents in the Market for Electric Vehicles: Opportunities and Incentives for Sustainable Innovation	EV	Global car manufacturer data	2012	Mann-Whitney U Test
Vergis and Chen (2015)	Comparison of plug-in electric vehicle adoption in the United States: A state by state approach	BEV, PHEV	US states	2013, yearly	Stepwise linear reg.
Chen et al. (2015)	Where are the electric vehicles? A spatial model for vehicle-choice count data	EV (BEV, PHEV, HEV)	Pennsylvania, 1000 census blocks	2012	Spatial analysis
Bansal et al. (2015)	Hybrid electric vehicle ownership and Fuel Economy Across Texas: An application of spatial models	HEV	Texas counties	2010	Spatial analysis
Mersky et al. (2016)	Effectiveness of incentives on electric vehicle adoption in Norway	BEV	Norwegian municipalities	2000-2013, yearly	Stepwise linear reg.
Zhang et al. (2016b)	The impact of car specifications, prices and incentives for battery electric vehicles in Norway: Choices of heterogeneous consumers	BEV	Norwegian municipalities	2011-2013, yearly	Random coefficient discrete choice model

Zhang et al. (2016a)	Consumer-oriented policy towards diffusion of electric vehicles: City-level evidence from China	EV	China, 88 pilot cities	2013-2015, yearly	Pooled OLS
Chang et al. (2016)	How are new-energy vehicle sales affected by government support? U.S. geospatial evidence	HEV	US country	2005-2007, quarterly	FE panel data reg/ Spatial analysis
Wang et al. (2017a)	Assessment of the incentives on electric vehicle promotion in China	BEV, PHEV EV	Chinese cities	2013-2014, yearly	Stepwise linear reg.
Li et al. (2017)	The market for electric vehicles: Indirect network effects and policy design	PEV	US metro areas	2011-2013, quarterly	FE panel data reg./ GMM
Kim et al. (2017)	Does driving range of electric vehicles influence electric vehicle adoption?	BEV	31 Global countries	2011-2015, yearly	RE panel data reg.
Dimatulac and Maoh (2017)	The spatial distribution of hybrid electric vehicles in a sprawled mid-size Canadian city: Evidence from Windsor, Canada	HEV	Windsor, Ontario Canada	2010	Spatial analysis
Soltani-Sobh et al. (2017)	Analysis of the Electric Vehicles Adoption over the United States	EV	US, 19 states	2003-2011, yearly	FE & RE panel data reg.
Ma et al. (2017)	An evaluation of government incentives for new energy vehicles in China focusing on vehicle purchasing restrictions	PEV	China, 6 cities	2011-2016, monthly	Panel co-integration
Heidrich et al. (2017)	How do cities support electric vehicles and what difference does it make?	EV	UK, 30 cities	2015	Wilcoxon rank sum test/ Cross sectional OLS
Morton et al. (2017)	Exploring the effect of local transport policies on the adoption of low emission vehicles: Evidence from the London Congestion Charge and Hybrid Electric Vehicles	HEV	UK, lower tier location	2012	Spatial analysis Cross sectional reg.
Liu et al. (2017)	Spatial effects on hybrid electric vehicle adoption	HEV	US, Ohio	2001-2012, yearly	Spatial analysis
Sheldon and De-Shazo (2017)	How does the presence of HOV lanes affect plug-in electric vehicle adoption in California? A generalized propensity score approach	PEV	California, census tract	December 2013	Generalized propensity score
Palmer et al. (2018)	Total cost of ownership and market share for hybrid and electric vehicles in the UK, US and Japan	HEV	UK, US, Japan	1997-2015, yearly	FE panel data reg.
Jenn et al. (2018)	Effectiveness of electric vehicle incentives in the United States	PEV	US states	2010-2015, monthly	FE panel data reg. GMM with LDV

Egnér and Trosvik (2018)	Electric vehicle adoption in Sweden and the impact of local policy instruments	BEV	Sweden, Municipalities	2010-2016, yearly	FE panel data reg.
Morton et al. (2018)	The spatial pattern of demand in the early market for electric vehicles: Evidence from the United Kingdom	PEV	UK, lower-tier location	2016	Spatial analysis
Narassimhan and Johnson (2018)	The role of demand-side incentives and charging infrastructure on plug-in electric vehicle adoption: Analysis of US States	PEV, BEV PHEV	US states	2008-2016, quarterly	FE panel data reg./ GMM with LDV
Yan (2018)	The economic and environmental impacts of tax incentives for battery electric vehicles in Europe	BEV	28 European countries	2012-2014, yearly	FE panel data reg.
Wee et al. (2018)	Do electric vehicle incentives matter? Evidence from the 50 U.S. states	PEV, BEV PHEV	US states	2010-2015, semi-annual	FE panel data reg.
Zambrano-Gutiérrez et al. (2018)	The Role of Public Policy in Technology Diffusion: The Case of Plug-in Electric Vehicles	PEV	US states	2010-2016, yearly	FE panel data reg.
Zhou and Li (2018)	Technology Adoption and Critical Mass: The Case of the U.S. Electric Vehicle Market	PEV	US metro areas	2011-2013, quarterly	FE panel data reg.
Wang et al. (2019)	A global comparison and assessment of incentive policy on electric vehicle promotion	BEV, PHEV	Global countries	2015	Cross sectional OLS
Rietmann and Lieven (2019)	How policy measures succeeded to promote electric mobility – Worldwide review and outlook	PEV	20 Global countries	2017	Covariance-based SEM
Münzel et al. (2019)	How large is the effect of financial incentives on electric vehicle sales? – A global review and European analysis	PEV	32 European countries	2010-2017, yearly	FE panel data reg.
Qiu et al. (2019)	Assessing the effectiveness of city-level electric vehicle policies in China	EV	China, 88 pilot cities	2014-2015, monthly	RE panel data reg./ GMM with LDV
Li et al. (2019)	Effect of policy incentives on the uptake of electric vehicles in China	EV	China, 43 cities	2011-2017, yearly	Pooled OLS
Clinton and Steinberg (2019)	Providing the Spark: Impact of financial incentives on battery electric vehicle adoption	BEV	US states	2010-2014, quarterly	FE panel data reg.

Kim and Heo (2019)	Key drivers behind the adoption of electric vehicle in Korea: An analysis of the revealed preferences	PEV	Korea, 16 metro municipalities	2013-2017, yearly	Negative binomial reg.
Guo et al. (2020)	Does air pollution stimulate electric vehicle sales? Empirical evidence from twenty major cities in China	EV, BEV HEV	China, 20 cities	2018, monthly	FE panel data reg.
Wang et al. (2020)	What influences sales market of new energy vehicles in China? Empirical study based on survey of consumers' purchase reasons	Top ten NEV models	China	2018	Correlation
Wee et al. (2020)	EV driver characteristics: Evidence from Hawaii	PEV	Hawaii	2011-2018, yearly	FE panel data reg.

Note: Categories are based on Münzel et al. (2019).

PEV = Cumulated BEV & PHEV data.

EV = Not clearly defined in paper.

3.3.2.1 Statistical Approaches

A variety of statistical approaches has been applied in this strand of literature to investigate the influence of various factors on EV market data. An overview that summarises all statistical approaches that have been identified through the SLR can be seen in Figure 3.12.

Due to the relatively recent introduction of EVs to the mainstream market, one of the major barriers for an econometric analysis of EV market data was the lack of observations over time (Kim et al., 2017). As a consequence, to obtain a sufficient sample size, early studies have predominantly relied on cross sectional analysis. The restraining influence of the short presence of EVs on the mainstream market and the lack of market data becomes even clearer when considering that no study has been executed that solely employed time series data.

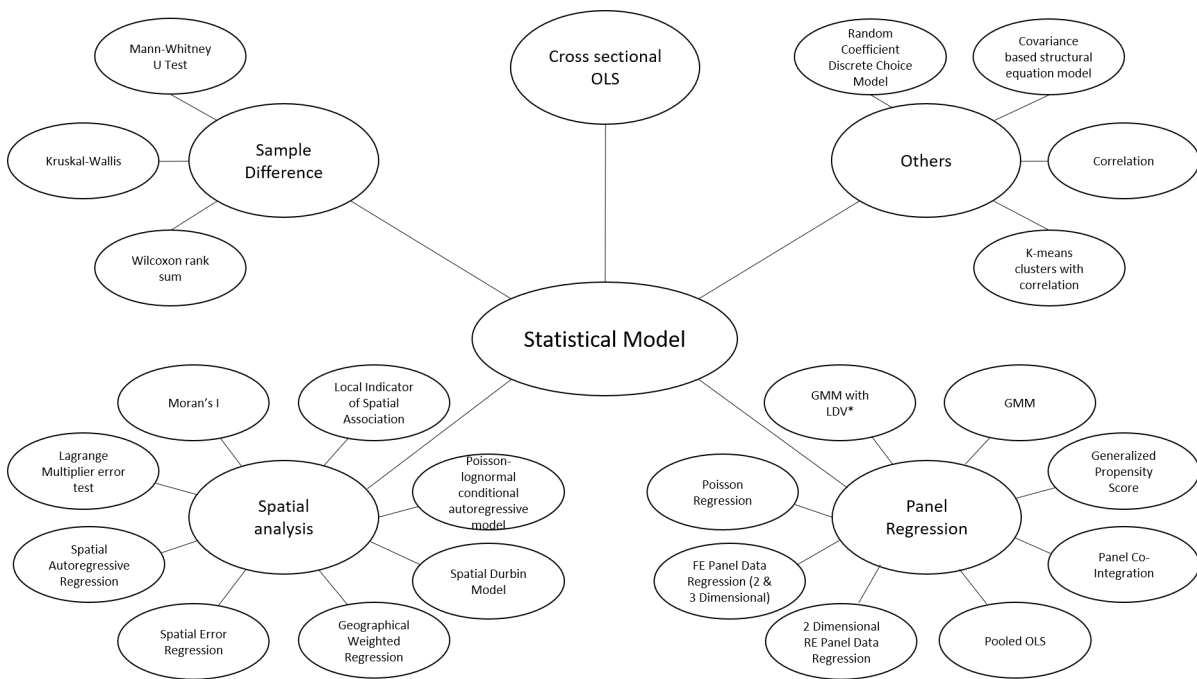
Taking advantage of the ability to process time series data of different entities, most studies employed panel data regressions. These models do not only provide the ability to substantially enlarge the sample size but also help to overcome certain problems such as multicollinearity or omitted variable bias (Soltani-Sobh et al., 2017). In the category of panel data regressions, it can be noticed that some investigations applied a three dimensional instead of a two dimensional model, by not only collecting data for several countries or regions over time but also for different car models. In doing so, the studies benefited from even more observations (e.g. Narassimhan and Johnson, 2018; Gallagher and Muehlegger, 2011; Yan, 2018). Furthermore, the authors were able to investigate differences in the impact of market drivers on different car models such as luxury or sport EV models (Chandra et al., 2010). Some studies have also applied a GMM with a lagged dependent variable to account for the influence of network externalities and the natural growth of new technologies (Jenn et al., 2013). Furthermore, the inclusion of a lagged dependent variable and the application of a GMM is used to help overcome a potential endogeneity problem between EV sales and infrastructure or incentives (Jenn et al., 2018).

Another widely applied statistical approach in this strand of literature is spatial analysis. For this analysis mostly geo-referenced data for a country or state has been obtained in lower-tier form to draw conclusions from the census tract of the regions on EV adoption. As previously discussed, by applying spatial analysis on lower-tier sectors, the authors were able to better explain the influence of socio-demographic variables on the market. In addition, by including an interaction

term or a spatial lag of the dependent variable in the regression, this method is suitable to investigate a potential neighbouring effect of EV adoption that can be hypothesized based on the theory of planned behavior (Morton et al., 2018; Rezvani et al., 2015).

Other methods such as methods to compare sample differences or correlations will not further be discussed, are, however, illustrated in Figure 3.12.

Figure 3.12: Statistical Approaches



Notes: *Lag dependent variable.
Some applied statistical subcategories are not explicitly illustrated.

3.3.2.2 Variables

In this section a closer look is laid upon the variables investigated in the identified literature. A comprehensive list of the variables can be found in Table 3.3. These variables can broadly be assigned to the seven different categories illustrated in Figure 3.8, namely the *Automobile sector*, *Incentives*, *Socio-economic/Socio-demographic*, *Infrastructure/Geography*, *Energy prices*, *Development EV* and *Psychological*. For a more detailed explanation of these categories please refer to Chapter 3.2.2.1.

As discussed above one of the most thoroughly investigated determinants in this research stream are incentives. This is also reflected in the range of different

variables that have been analysed. Incentives can broadly be categorized into two sub-categories, namely, financial and non-financial incentives. While financial incentives are often measured as a ratio (e.g. Sierzechula et al., 2014; Münzel et al., 2019), non-financial incentives are commonly included as a binary variable in the analysis (e.g. Zhang et al., 2016a; Qiu et al., 2019). The incentives included in the analyses of a study thereby strongly depend on the geographic scope of the investigation as different countries or even cities within a country grant different subsidies. This can sometimes also be traced back to different market regulations. Using the variable *license plate* as an example, this factor has only been considered in studies with a focus on Chinese cities. As some Chinese cities encounter high air pollution, local governments are limiting the distribution of license plates which takes place through a lottery. To incentivise the adoption of EVs, however, the disposal of license plates for this vehicle type is not restricted (e.g. Li et al., 2019; Wang et al., 2017a). Consequently, the investigation of this variable is limited to China.

Another group of variables that has often been considered in the identified literature are socio-demographic and socio-economic variables. *Income* for example has been included in 30 of 42 statistical analyses and therefore represents the most frequently investigated variable. As Kumar and Alok (2020) has already pointed out, the significance of these variables differ based on the investigated region because of, for example, different cultures. Studies from the identified literature that have frequently included variables from this category are spatial analyses. These studies mostly employed census tract data provided by official sources (e.g. Dimatulac and Maoh, 2017; Morton et al., 2018). An advantage of this method compared to for example surveying EV owners could be to circumvent a potential sampling bias. Socio-demographic and economic variables are also often used as control variables to account for diverging living conditions (Münzel et al., 2019).

A group of variables that has experienced great academic interest in studies that investigated intention to adopt EVs (Rezvani et al., 2015; Liao et al., 2017) but lacks research in regard to actual adoption measured with market data is psychological factors. A potential explanation for this phenomenon is the difficulty to find data that can be used to generate a variable which can adequately represent psychological factors on a market level. However, the importance to find more objective and innovative measurements of psychological factors is stressed by the potential compromising influences of biases that can be a result of data collection

by means of surveys.

First attempts to investigate the influence of environmentalism, however, can be noticed. Thereby, measures such as memberships in an environmental club (Gallagher and Muehlegger, 2011), green party votes (Zambrano-Gutiérrez et al., 2018) or an existing environmentalism index (Sierzechula et al., 2014) have been used to represent a country's or society's level of environmentalism. These measures are good initial approaches but leave room for improvement in regard to their ability to actually capture environmental awareness which has been found to be a relevant determinant of the intention to purchase an EV.

Interestingly a variable that to the best of my knowledge has not been investigated based on actual market data in relation to EV adoption is the level of a countries or societies innovativeness. The significance of this factor has been determined by several scholars in relation to EV purchase intentions and therefore, might be of interest for future research (e.g. Liao et al., 2017; Rezvani et al., 2015; Kumar and Alok, 2020).

Table 3.3: Variables

Automobile Sector		Incentives		Socio-economic/ Socio-demographic		Infrastructure/ Geography	
EV producer global HQ in country	1	Financial incentives	24	Income	30	Charging Infrastructure	21
Vehicle stock	5	Tax incentives		80-20 income ratio	1	Normal chargers	
Vehicle growth	1	Income tax credit		Gini-coefficient	1	Fast chargers	
EV model imported	1	Sales tax incentive		National purchasing power	1	No. of grocery stores	2
City with automobile industry	1	Home charger subsidy		Industrial development (GDP)	2	Miles roadway	1
Hybrid vehicle sales	3	Registration fees		VAT	1	Attractiveness charging infra.	1
Car registrations	1	Emission inspection fee		House Value	1	Weather	2
EV registrations	1	Research & Development		Local number jobs	1	Air pollution	1
CO ₂ transportation sector	1	Attractiveness financial incentives		Share of worker in industries	1	Local traffic flow	1
		Corporate Fuel Economy Standard		Gender	5	Local car pollution	1
		Toll waivers		Age	8	Distance to city centre	1
		Purchase incentive		Race	4	Proximity to major city	2
		Non-financial incentives	22	Population	15	Renewable Energy	1
		Urban Roads		Unemployment	8		
		License Plate		Tertiary education	14		
		No purchasing restrictions		Secondary education	5		
		Parking Benefits		Licensed Drivers	1		
		Policy to help finding chargers		Commuting mode	3		
		HOV lane access		Commute minutes	5		
		Model development award		Commute distance	1		
		Manufacturing award		Car driver to work	6		
		Knowledge about tax credit		Carpool to work	2		
		HOV access * HOV density		Company car	1		
		Attractiveness non-financial incentives		Share uses public transport	1		
		Pilot city for incentives		Vehicle miles traveled	6		
		City has climate change strategy		Number cars per household	4		
				Urban density	1		
				Rented apartment	1		
				Home ownership rate	2		
				Number of households	2		
				Resident worker density	1		
				Residents in a household	6		
				Workers per household	1		
				Self-employed	1		
				Gender*Health occupation job	1		
				Dwelling type house	1		
				Semi-detached house	1		
				Land use balance	1		

Table 3.4: Variables Continued

Energy Prices		Development EV		Psychological	
Fuel costs	20	Number EV models available	5	Environmentalism	
Electricity prices	8	Year that EV first sold in country	1	Member environmental club	1
Annual fuel savings	2	EV price	5	Environmentalism index	3
		Relative price of EV to ICC	1	Democrats in legislature	1
		Total cost of ownership	1	Green party victories	1
		Driving range	4	Green party votes	3
		Motorisation rate	1	Advertising campaign	1
		Fuel efficiency	2	Electric vehicle awareness	1
		Patents	1	Spatial term for zone (Neighbouring)	1
		Top speed	1	Spatial lag of EVs (Neighbouring)	5
		Number of seats	1	Public procurement of EVs	1
		Battery capacity	1		

Note: Wang et al. (2020) is excluded.

For incentives only the most frequently used incentives are listed.

Grocery stores was often used as an instrumental variable.

Neighbouring was measured as a spatial lag of the dependent variable.

Network effects was measured by a lag of the dependent variable.

3.3.3 Conclusion of the Systematic Literature Review

This SLR has focused on studies that have statistically investigated the influence of determinants on the EV market by using actual market data. Thereby, it has shown that the investigations significantly differ based on their level of geographic dispersion but most research has focused on a limited number of countries. Furthermore, due to an increase in data availability the research focus has shifted from the vehicle type HEV to BEV and PHEV. It was also found that a variety of statistical methods has been applied to overcome certain limitations or as they are more suitable for the investigation of certain variables. When looking at the considered variables, a general research focus on the determinants of the categories *Incentives* and *Socio-demographic/economic* can be noticed. In contrast, the category *Psychological* factors seems to be underexplored. Therefore, this research proposes to explore more innovative ways of measuring psychological factors and testing the significance of their effect on actual sales data.

3.4 Psychological Factors and the Electric Vehicle Market

This thesis investigates two psychological factors that potentially impact the EV purchasing decision, namely, environmental awareness and innovativeness. In the following, the extant literature in the field of EVs is reviewed to provide an overview of the status-quo of research on these two determinants and outline the research gap. The identified underlying theories and previous findings facilitate the development of hypotheses for each of the investigated research questions.

3.4.1 Environmental Awareness

Since EVs are considered to be a more environmental friendly transportation mode compared to ICCs, a determinant of the EV market that immediately comes to mind is the level of environmental concern or awareness of a person or society. It is, thus, not surprising that research exists, which has already attempted to determine the influence of EA on the adoption of EVs. This literature stream will be reviewed in the following sub-chapter. Thereby, a special focus will be laid upon the measurement of EA applied in this and related streams of research. As previously elaborated, there are only a few studies that have investigated the influence of EA

on the EV market by using actual market data. Thus, most of the studies analysing this relationship might be exposed to the attitude-action gap or the biases that prevail in this research context. A brief review of the mainstream state of the art knowledge will, nevertheless, take place to provide the reader with an idea of the findings and on how the influence of EA on the EV market has previously been analysed.

3.4.1.1 Previous Literature on Electric Vehicle Adoption Intention

Drawing on the property of EVs reduced CO_2 emissions, researchers have applied different theories to justify EA as an important factor that could influence an individual's intention to adopt an EV. A few of the most commonly used theories to justify this relationship are for example the TPB (Yadav and Pathak, 2016; Adnan et al., 2017; Zhang et al., 2018b), value-belief-norm theory (Jansson, 2011; Axsen et al., 2012) or a theory that refers to symbolic motives and self identity (Skippon and Garwood, 2011; Axsen et al., 2018). Based on the TPB for example, researchers argue that people's attitudes towards EVs should be positively influenced by their environmental concerns, due to the EV's reduction of CO_2 emissions (Zhang et al., 2018b). Furthermore, they argue that the aspect of social pressure of the TPB might also support the pro-environmental behavior and thus the intention to purchase an EV (Yadav and Pathak, 2016; Zhang et al., 2018a). If an individual for example lives in a neighborhood or has family members or friends that pay great attention to environmental aware behavior, it might experience the pressure to adapt to this behavior and is thus more prone to purchase an EV. Self identity motives are utilised in this stream of literature to argue that people want to express their pro-environmental lifestyle through the acquisition of EVs (Axsen et al., 2018). Having a strong theoretical background that links intentions to actual behavior is especially important in studies investigating purchase intentions to at least partially allow the transferability of the findings on intention to actual adoption behavior.

The predominant application of surveys as the methodology for data collection to investigate the influence of EA on EV purchase intention can have several rationales. The two most apparent reasons are the focus on adoption intention and the property of EA as a psychological factor. As previously discussed, EVs have only recently entered the mainstream market providing only a limited number of market data observations. Thus, investigating adoption intention has been the easiest way

to obtain a sufficient sample size due to not being limited to the population of EV owners. In addition, intention can in general not be observed, therefore making surveys the most viable option for investigating intention. Furthermore, it is difficult to measure a psychological factor such as EA as there are no objective measurable values of such factors. Consequently, the easiest and most commonly applied source to determine the psychological determinant EA is by surveying people and drawing conclusions on their level of EA. Although researchers that have focused on intention to adopt EVs almost exclusively applied surveys as a data collection method, the research methodology in terms of how EA has been measured differs between the studies. Two common approaches to assess EA are by either asking the survey respondents questions that allow a direct assessment of their attitude towards the environment (e.g. Axsen et al., 2012, 2015; Carley et al., 2013) or by asking questions about environmental oriented behavior that allow an indirect assessment of the individual's level of EA (Ziegler, 2012; Axsen et al., 2016). Questions of the former category range from the respondent's answers about his or her general concern about environmental problems (Lai et al., 2015) to more complex questions such as the subjective assessment on how fragile nature is (Axsen et al., 2012). While in several papers, the questions or statements of the surveys to assess the respondents environmental concerns are developed by the researchers themselves (Carley et al., 2013), a few also use existing frameworks such as the New Environmental Paradigm scale (Axsen et al., 2012, 2015) developed by Dunlap et al. (2000). Questions about environmental oriented actions are for example whether the respondent engages in environmental conservation meetings (Axsen et al., 2016) or actively recycles (Chu et al., 2019). For both categories, a scale is often applied on which survey participants should indicate how much they agree or disagree with a statement or question. An alternative measurement approach is to let participants award a certain amount of points based on how much they think a statement is true or represents their behavior. From a methodological perspective a whole range of different approaches has been applied to analyse the influence of EA on EV adoption. While some exploratory studies focused on solely reporting the percentages of how much people agree with a statement (Skippon and Garwood, 2011; Egbue and Long, 2012; Graham-Rowe et al., 2012) to provide an idea which factors can potentially influence the EV market, other researchers applied more advanced statistical analyses. Examples include Multinomial Probit Models (Ziegler, 2012), Multinomial Logit Models (Nie et al., 2018) or structural

equation models (Wang et al., 2017b) which are employed to not only investigate the significance of the determinants but also report the degree by which a change in the determinant influences the individual's attitude or purchase intention towards an EV.

Previous research reports mixed results about the significance of EA on the adoption intention of EVs (Coffman et al., 2017). The majority of the studies, however, have found a positive influence of pro-environmental attitudes towards EV adoption intention. Analyses that report a significant positive influence of environmental concerns on EV adoption intention are for example Schlüter and Weyer (2019) or Zhang et al. (2018b).

Evidence for the opposite that EA does not significantly influence adoption intention of EVs, has also been found by researchers in this field. Graham-Rowe et al. (2012) for example carried out a qualitative analysis using semi-structured surveys. In the context of the survey, 40 UK non-commercial drivers were interviewed regarding their opinion about factors such as cost minimisation, vehicle confidence or environmental beliefs. Prior to answering the survey, the participants were required to test drive an EV. Thereby, 20 were able to test drive a BEV and 20 a PHEV. The responses of the participants, indicate that they doubt the environmental benefits an EV provides compared to an ICC. They for example questioned the sustainability aspect of the generation of the electricity or the materials the batteries are made of. According to the authors, car drivers weigh greater importance on other car attributes and the personal utility a car provides than on environmental concerns.

A prior study executed by Hidrue et al. (2011) has found similar results about the subordinate role of environmental benefits EVs provide. Although, the researchers have found that people are in general willing to pay more for a reduction in pollution, the value they assign to this car attribute is significantly lower compared to other performance related car properties of EVs such as driving range, fuel cost savings or charging time. While people assign a monetary value of a 50% pollution reduction of about \$1,900, a 95% reduction of pollution is worth over \$4,300. To put these values in context, an increase of the driving range of EVs by 150, 200 or 300 miles is valued with an weighted average amount of \$5,646, \$9,289 and \$12,779, respectively.

Another interesting study that raises doubt about the significant influence of EA on the EV market has been executed by Smith et al. (2017). The authors

conducted a best-worst stated choice experiment with six choice replications. In this experimental setting, survey respondents were required to select their preferred and least preferred vehicle type between BEVs, PHEVs, Petrol and Diesel vehicles. The attributes of the cars and market conditions, however, changed in each replication. The results show that 10.9% of the respondents select EVs as their preferred vehicle type for all replications. The authors conclude that for most of these non-traders, social desirability bias had a strong impact on not changing the vehicle choice.

As discussed in chapter 3.2.2.2, the attitude-action gap is one of the major limitations to the ability to draw conclusions of intention studies on actual adoption behavior. This is especially the case when analysing the influence of a determinant in regard to the environment. Studies presented in chapter 3.2.2.2, such as the study of de Rubens (2019) have shown that analysing intention behavior could result in misleading interpretation of the effect of EA on EV adoption. Thus, in the subsequent sub-chapter a review of EV adoption studies will take place.

3.4.1.2 Previous Literature on Electric Vehicle Adoption

Based on the data collection approach, previous literature that has investigated EV adoption, can be divided into two groups. While the first group applied surveys of EV owners to collect data for the analyses, the other group considers EV market data for their investigation. Amongst others, research that relies on surveys and investigated the impact of environmental concerns on EV adoption has for example been conducted by Axsen et al. (2016, 2018) or Chu et al. (2019).

Axsen et al. (2016) for example employed an existing data set, which is the Canadian Plug-in Electric Vehicle Study, to compare characteristics of EV owners with people who state an intent to purchase one. In regard to the characteristic of EA, the researchers have found that EV owners compared to potential EV adopters exhibit significantly higher levels of environmental concern and environmental engagement. Taking advantage of the same data set, Axsen et al. (2018) have conducted 17 semi-structured interviews with EV owners. The researchers have found that the survey participants in general exhibit an interest in environmental protection.

A recently published study by Chu et al. (2019) also provides evidence for the significance of the influence of EA on EV adoption. In their analysis, the authors focused on the countries China and Korea and investigated whether the purchase

reasons of an EV differ based on the country. To evaluate the level of environmental concern, the survey participants were asked nine different questions regarding representative environmental behavior or attitude towards environment related topics. The results of the investigation have shown that EV owners in China exhibit significantly higher environmental concerns than Korean EV owners. In a consecutive analysis, the researchers have analysed the reasons behind the decision of purchasing an EV, providing the survey participants with four alternatives: environmentally friendly reasons, economic reasons, innovativeness of EV and reputation and interest from others. The results of the analysis indicate that while environmental reasons were the most important for a Chinese EV adopter, the importance of environmental concerns for a Korean EV adopter was only on third place, behind economic and innovativeness factors. Determining the marginal impact of these four determinants on usage satisfaction of an EV, Chu et al. (2019) ran a linear regression with three additional variables accounting for income, charging frequency and daily use time. The analysis reveals that environmental reasons significantly affect user satisfaction in both countries. The higher coefficient for Chinese survey respondents however implies an even stronger influence of environmental reasons in this country.

As elaborated in a previous chapter, using surveys as a data collection method can however be exposed to certain biases. Thus, it could be insightful to review studies of the second group, studies that employed actual market data, if they confirm the findings of the survey studies. In the course of the systematic literature review, seven studies were identified that investigated the influence of EA on EV adoption by using market data. The measurement of EA applied in these studies can thereby be divided into two groups. While the research that can be assigned to the first group uses existing environmental indices (Sierzechula et al., 2014; Vergis and Chen, 2015; Wang et al., 2019), research of the second group utilizes voting outcomes for their measurement of EA (Sheldon and DeShazo, 2017; Egnér and Trosvik, 2018; Zambrano-Gutiérrez et al., 2018; Clinton and Steinberg, 2019).

Sierzechula et al. (2014) in their study, employed the Environmental Performance Index established by Yale (2021) to measure a country's level of EA. The index considers different performance indicators to measure the environmental performance and regulations of nations and ranks country's based on these. Running a cross sectional analysis of 30 countries for the year 2012, the researchers found that a country's environmentalism score does not significantly influence the market share

of EVs. In a later study executed by Wang et al. (2019), the same index has been used for the measurement of EA. The authors of this study also performed a cross country analysis for 30 countries in the year 2015 and confirmed the insignificant influence of this determinant. Another research that applied an environmentalism index as a surrogate variable for EA was performed by Vergis and Chen (2015), who focused their investigation on the US for the year 2013. The authors utilized the Green Planning Capacity Index, which measures the environmental management and green planning abilities of a state. This index is comparable to the index applied by Sierzechula et al. (2014) and Wang et al. (2019) only on state level. The results of this investigation are in line with the other two studies and indicate an insignificant influence of this factor on the market share of EVs.

A different approach to measure environmental awareness has been applied by Egnér and Trosvik (2018). The researchers exploit green party votes of a recent election in Sweden to measure the level of EA on municipality level. In a longitudinal study covering the years 2010-2016, the results, in contrast to the other studies, indicate a significant positive influence of EA on the EV market. Although, Egnér and Trosvik (2018) conducted a longitudinal study, the measurement of EA in this study is not over time as it only considers election results of one year. A similar approach to measure EA was applied by Clinton and Steinberg (2019), who focused on the US states between 2011 and 2015. The researchers developed an index based on the voting records of each state's members of Congress. The results show that EA in this study is significantly positive at a 10% level. Another study that focuses on the US and applied an EA measure based on political votes was carried out by Zambrano-Gutiérrez et al. (2018). In this study, the level of EA was measured in two ways. The authors used the percentage of Democratic legislators in the Senate and House of Representatives as well as victories of members from the Green Party to determine the level of EA in the respective states. The results of this longitudinal study, that covers the years from 2010-2016, show that neither EA surrogate exhibits a significant influence on the EV market. The last study that was identified with the help of the SLR, was carried out by Sheldon and DeShazo (2017). Focusing on California census tract data over a time period spanning from 2010 to 2013, the authors utilized the results for the vote of the suspension of the "Global Warming Solutions Act of 2006" to measure EA. The underlying assumption in this approach was that the larger the share of "yes" votes in a census, the lower the level of EA in the region. The results of the analysis corresponds with the majority

of the findings and indicate no significant influence of EA on the EV market.

These seven articles are, to the best of my knowledge, the only studies that have applied some kind of EA measure and investigated the impact on actual EV market data. While these approaches are good initial indicators, they also exhibit room for further improvement. For example, it might be useful to establish a measure that captures EA more continuously over time and focuses on the perception of the population. Furthermore, it would be beneficial to apply a measure that captures both, the frequency in which the society is confronted with a topic and in which the topic is discussed by individuals in the society. Another shortcoming of using voting results that has been explicitly mentioned by Egnér and Trosvik (2018), is that environmentally aware people do not necessarily vote for green parties or vote at all. These limitations suggest that it could be beneficial to investigate the relationship between EA and EV sales at a macroeconomic level by applying a more objective measure of EA that allows the investigation over a longer period of time and addresses the required improvements mentioned above. It should also be considered that EA is a psychological factor and therefore no direct measurement exists. Surrogate variables for EA can however deviate in their level of representativeness and accuracy. This can partially be caused by different definitions of EA or data availability. Different approaches can therefore capture different aspects of EA. Consequently, it makes sense to establish different and innovative measures of EA to obtain a more diversified view on the influence of EA on the EV market. In the following section an alternative measurement approach for EA will be presented, which is largely able to overcome the described limitations.

3.4.1.3 Measurement of Environmental Awareness in Related Streams of Research

Different ways of measuring public awareness or opinion towards a certain topic have been applied in academic literature as well as practice. As previously discussed, the most frequently used method to assess an individual's awareness are surveys. However, surveys are not the only way to capture the public's opinion.

Another method to measure awareness is to investigate the sources from which the general public obtains information. As the key function of mass media is to report to people an indirect awareness assessment is possible by looking at the publication frequency of the investigated topic (Olteanu et al., 2015). This inference

can be made as scholars discovered a significant correlation between public's opinion and mass media coverage (Besova and Cooley, 2009). Consequently, newspaper coverage has been used either supplementary to surveys or as a sole indicator for awareness. Thereby, this method can be applied to a wide range of topics. The employment of newspapers as an opinion barometer for example ranges from topics such as the interest in the OPEC (Plante, 2019) to economic uncertainty (Baker et al., 2016). Scholars, especially found interest in using newspapers as measures for EA (Sampei and Aoyagi-Usui, 2009; Olteanu et al., 2015). The advantages of applying an analysis based on newspapers instead of surveys are the better access to old reports due to databases and the simpler analysis by means of analytical software packages. However, this method also entails several downsides. As the investigation of newspapers is an indirect measurement of awareness, it might not accurately reflect the public's opinion. This becomes even clearer when considering that journalists have a deontological obligation to determine whether they can report about a topic (Olteanu et al., 2015).

A relatively new medium used to investigate public opinion that has received increasing academic interest over the last years is social media channels and in particular Twitter. According to the company's annual report, the "[...] *primary product, Twitter, is a global platform for public self-expression and conversation in real time*" (Twitter, 2019, p.7). Hence, the main purpose of Twitter is to share opinions. Furthermore, the social media platform has witnessed a worldwide growth in user numbers over the last years, allowing the conclusion of a global reach. This assumption can be further underscored as even politicians and supranational institutions use this medium to communicate and share information. Moreover, Shapiro and Hemphill (2017) found a significant influence of tweets from politicians on newspaper coverage. Their findings indicate that Twitter posts in some areas are replacing what formerly would have been communicated through press releases. Therefore, one can assume that topics discussed on Twitter will also reach a wider population, outside of the active Twitter users.

Twitter as an opinion barometer provides several advantages compared to the previously mentioned methods. First, data software particularly focusing on Twitter has been developed to analyse tweets, which enables more advanced analyses. Furthermore, Twitter provides access to a large sample that would not be as easily accessible otherwise. Based on the characteristics of a Twitter analysis discussed above, we can conclude that this measurement method can be a useful supplement

to combat the drawbacks when using surveys as a barometer for public opinion.

Twitter as a tool to measure public opinion and sentiment is also becoming increasingly popular in sustainability related research fields. For example Reboredo and Ugolini (2018) executed a sentiment analysis, which examined the influence of investor sentiment on renewable energy stocks, where Twitter was used as an investor sentiment proxy. There are also first studies which suggest that Twitter can be a useful tool in measuring EA (An et al., 2014; Cody et al., 2015). In addition, more and more databases with tweet IDs are being published that can be used to investigate public opinion regarding climate change (e.g. Samantray and Pin, 2019; Littman and Wrubel, 2019). Consequently, Twitter could be a promising method to measure EA in this field of research.

Another medium that has received widespread academic interest over the last years to measure the public's awareness towards a certain topic is Google Trends (GT). GT can be used as a surrogate since it can be assumed that search traffic reflects the interest of the public in a topic (Durmuşoğlu, 2017). GT is an eligible website for this purpose as it provides information on the search frequency of search terms entered into the most commonly used search engine Google. Google reports a market share for overall search requests in the world wide web of approximately 92% (StatCounter, 2021).

It is thus not surprising that GT has been used as a measure for various topics in academic literature. The application of this index ranges for example from the analysis of forecasting GDP development (Woloszko, 2020) to quantifying trading behavior in financial markets (Preis et al., 2013). Several researchers have also already taken advantage of the ability of GT to evaluate the public's level of environmental awareness for the investigation of different topics (Le Nghiem et al., 2016; Laico, 2018; Rousseau and Deschacht, 2020; Santi, 2021). Furthermore, Lineman et al. (2015) found a similar behavior regarding the search frequency for environmental search terms as has been uncovered for Twitter. Similar to tweet numbers, the researchers found that the search frequency of a topic is strongly related to its media coverage. Thus, its search score as reported by GT increases if an issue receives more exposure in mass media. Based on the fact that this method has been frequently used by previous research Santi (2021) concludes that GT is an established measurement method for EA.

In the research area of EVs, GT was also already employed. Vergis and Chen (2015) for example used the search frequency of EV models for the respective

countries considered in their study to gauge the general public's awareness of EVs. Considering that GT has been utilised by various researchers to measure EA, this method seems to be appropriate as a second index for the analysis in Chapter 6.

3.4.1.4 Research Hypothesis

As it becomes evident from the reviewed literature, the relationship between EA and the EV market is not as obvious as one might initially expect. While the majority of previous research focusing on intention to adopt EVs indicates that EA positively influences the EV market, some studies in this stream raise initial doubts about the significance of this factor and provide evidence for the opposite, i.e. the insignificant influence of this determinant. Moreover, the limited research that analyses actual adoption behavior, the importance of which is driven by the attitude-action gap, exhibits mixed results and even tends to support the assumption of an insignificant influence of EA on the EV market. However, as elaborated above the validity of the previously applied measurements of EA is questionable and as EA represents a psychological factor, additional research applying different and innovative measurements of EA contribute to obtain a more comprehensive picture of the influence of this factor.

Considering, the theories that can be applied to justify the relationship between EA and the EV market, they strongly support the hypothesis of a significant influence of EA. According to the TPB an increase in environmental awareness should not only positively influence the attitude towards an EV but also a general increase in the society's environmental concern could lead, based on the social norm dimension, to a surge in EV adoption. Furthermore, using the symbolic motives theory, it could be assumed that people might use EVs to express their environmental supporting behavior and thus an increase in EV adoption should be noticed. Based on the theoretical support and the findings of previous research on EV adoption intention, the hypothesis tested in Chapter 6 is:

Hypothesis 3.1.

H₀: Environmental awareness does not significantly and positively influence the EV market.

H_A: Environmental awareness significantly and positively influences the EV market.

Supported by the attitude-action gap, the research question will be investigated

on a macroeconomic level, applying two different and innovative gauges of environmental awareness. In particular, a Twitter keyword and Google Trends analysis will be executed.

3.4.2 Innovativeness

Another more self-centered psychological factor that has witnessed considerable academic interest in explaining the reasons behind EV adoption intention is innovativeness. However in the course of the SLR, no study was identified that has investigated the influence of a person's or country's innovativeness level on the EV market, using actual market data. Similar to the investigation of the relationship between EA and EV adoption, researchers predominantly rely on surveys and other qualitative measures to determine the influence of this factor on the EV market, thereby limiting the research mostly to adoption intention. Based on the biases and the attitude-action gap in this market, there is clearly a lack of research investigating this relationship on a macroeconomic level. However, to obtain insights about the findings in this strand of literature and to develop adequate research hypothesis, it makes sense to briefly review some of the core studies in this field. Consequently, a brief review of the findings in this research field takes place in the following. Moreover, measurements of innovativeness employed in different studies are discussed. Finally, this part of the literature review concludes with different research hypothesis which will be investigated in Chapter 7.

3.4.2.1 Extant Literature on the Influence of Innovativeness on Electric Vehicle Purchase Behavior

Considering that EVs are regarded an eco-innovation (Jansson, 2011; Sierzechula et al., 2012; He et al., 2018) as well as a possible disruptive new technology on the market, a relationship between innovativeness and EV adoption seems to be evident. Nevertheless, researchers have also supported the investigation of the influence of innovativeness on EV purchase intention by employing different theoretical backgrounds. Two of the most commonly applied theories to justify the connection between innovativeness and EV adoption are the concept of symbolic motives as well as the DOI theory. Scholars that employed the former concept claim that innovative people would purchase an EV, since driving such a vehicle type would express and signal their innovative personality (Schuitema et al., 2013; Noppers et al., 2014;

Schlüter and Weyer, 2019). Based on the DOI theory on the other side it could be argued that innovative people are the first to adopt a new technology as they are the most curious to test new ideas and innovations (He et al., 2018). When recalling the *Diffusion of Innovation Curve* depicted in Figure 3.6, the population is divided into groups based on how quickly they adopt a new technology, defining people who adopt new technologies earlier as more innovative. Thus, as EVs can be seen to present a new technology in the transportation sector (Plötz et al., 2014; Morton et al., 2016), it is argued that innovativeness is also a decisive factor in the formation of a purchase intention for potential customers in the current market situation (He et al., 2018). Another advantage of the DOI framework is that it provides guidance on how to measure the level of an individual's innovativeness. This is especially useful in the development of questionnaires for surveys which are the predominant method of data collection in this research stream as it can help determine valid constructs that capture innovativeness. Morton et al. (2016) for example measured the innovativeness level of the survey respondents in their research by employing several questions that reveal insights about specific sociological behaviors, which based on Rogers (2003) reflect the innovativeness level of an individual.

Another large part of the literature in the field of research focusing on the drivers of early adopters of EVs and those who intend to purchase such a vehicle type, often use the DOI theory to establish the underlying assumption that people who purchased an EV early on are bound to be innovative. Therefore, rather than measuring these people's innovativeness, these studies aim to identify the specific characteristics of this group to help establish an understanding of EV adoption behaviors and derive implications for the diffusion of this new technology on the market. In this context, it is not directly investigated whether innovativeness as a determinant exhibits an influence on the adoption of EVs but the characteristics that innovative people have in common based on the DOI theory (Peters and Dütschke, 2014). These investigations that are based on the DOI theory are not limited to the investigation of sociological determinants of the individuals but can also expand to how they perceive an innovation as examined in the study of Jansson (2011) or Peters and Dütschke (2014). In the study of Jansson (2011), the researcher examined whether the perception of the five key characteristics of an innovation, discussed in Chapter 3.2.1.3 (e.g. relative advantage, compatibility etc.), are perceived differently by the people who bought an alternative fuel vehicle (AFV) compared to those who did not. Thus, by investigating the characteristics

in this research setting, Jansson (2011) presumes that AFV adopters are more innovative and therefore perceive the advantages of these characteristics to be more significant.

To build on this point, the DOI theory and in particular the five characteristics have also been used to assist in the interpretation of findings and help establish practical guidance. For example Schlüter and Weyer (2019) found that EV car-sharing programs increase the acceptance of this vehicle type, which can potentially be caused by an improved *observability* and *trialability* when such vehicles are included in a car-sharing fleet. *Observability* and *trialability* are, based on the DOI, two key characteristics that an innovation should possess for a better diffusion in the market, wherefore the authors recommended that car-sharing companies should include more EVs into their fleet.

Focusing on the extant literature that particularly investigated the influence of the determinant innovativeness, in general a significant and positive influence stemming from an individual's innovativeness on its EV purchase intention was determined (e.g. Jansson, 2011; Schuitema et al., 2013; Plötz et al., 2014; Morton et al., 2016; He et al., 2018; Wang et al., 2018; Schlüter and Weyer, 2019). Conducting a survey in China, He et al. (2018) have found that personal innovativeness is one of the most important personality traits that influence the intention of an individual to adopt an EV. Moreover, the scholars have also found that innovativeness indirectly influences the intention to adopt an EV. Incorporating positive and negative perceptions as mediator variables between personal innovativeness and EV adoption intention in the analysis, the researchers have found that more innovative individuals more strongly perceive the positive utility from purchasing this vehicle type while recognising the negative utility to a lesser extent. Due to a significant influence of the mediator variables on the dependent variable of the investigation, an indirect influence of personal innovativeness can be concluded. In contrast to the majority of the studies, only a few studies have found that innovativeness is not a significant factor for explaining purchase intentions of EVs. One example for such a study is Tu and Yang (2019). In their investigation, a questionnaire was distributed among 120 Chinese consumers with the scope to develop a theoretical framework for the investigation of factors influencing the adoption intention of EVs. The determinant personal innovativeness in their research setting was hypothesised to positively influence the individual's attitude toward the behavior, which is one dimension of the TPB, and therefore indirectly influence the purchase

intention of an EV. Applying a structural equation model, the researchers found that personal innovativeness has no significantly positive influence on the attitude toward the behavior dimension. When looking at the applied interpretation of personal innovativeness in this study, which is the "... consumers' likelihood to accept electric vehicles faster than their friends" (Tu and Yang, 2019, p.8), it is strongly EV centered and does not provide a general and objective assessment of an individual's level of innovativeness independent from the product.

While in the course of the SLR, only a few studies were identified that investigated the relationship between EA and the EV market by using actual market data, no study was detected that employed market data for an investigation of the influence of innovativeness on the EV market. However, similarly to EA the predominantly applied method to collect data was surveys and in particular in most of the cases not people who have purchased an EV were questioned but people who did not own such a vehicle type. Therefore, the significance of determinants of this market was predominantly assessed based on the stated intent of potential future EV customers. One study that has analysed the influence of innovativeness on EV adoption and did not solely rely on a sample of non-EV owners was performed by Jansson (2011). As already discussed, Jansson (2011) collected data by means of survey's from people who own an AFV and from people who do not own such a vehicle type. To assess the innovativeness level of the individuals, questions are asked that evaluate how novelty seeking these people are. Determining whether AFV adopters are more innovative than non-AFV owners, the difference of the mean scores for this determinant is statistically tested for significance. The obtained results in this study, thereby suggest that AFV owners exhibit a higher level of innovativeness.

Another interesting study, that was already touched upon in this part of the literature review, was performed by Schlüter and Weyer (2019). In this research, the influence of different psychological as well as sociological determinants on EV adoption intention were investigated using the TAM framework for research guidance. Thereby, the authors discovered that people with a higher level of technophilia, which in their view represent the innovativeness level of the individuals, positively influences the dimensions perceived usefulness and perceived ease of use of this vehicle type and therefore indirectly EV adoption intention. Moreover, since one question of the survey was whether the respondents engage in car-sharing and if yes a further distinction between the propulsion system could be made, the

researchers were able to divide the sample into users and non-users of car-sharing. This allowed to extend the investigation and analyse whether car-sharing users are inclined to purchase an EV than people who do not engage in car-sharing. Confirming this hypothesis the researches also found out that a higher EV acceptance can especially be achieved when users of traditional car sharing services switch to EV car sharing services. In contrast, they did not find evidence that car-sharing users are more technophil than non car-sharing users.

In the study of Schlüter and Weyer (2019), the relationship between technophilia and EV adoption intention is argued based on the symbolic motive concept as it can be assumed that technophil individuals would purchase such a car to express their personality. A study that also assigns a high value to symbolic motives was performed by Schuitema et al. (2013). The authors claim that symbolic motives are one of the three main motivational dimensions of consumer innovativeness. The other two dimensions are instrumental and hedonic motives. While symbolic motives as already discussed refer to the expression of the individual's identity, instrumental attributes focus on the utility and functionality the innovation provides a potential customer. Lastly hedonic innovativeness is according to Schuitema et al. (2013) concerned with the emotions the adoption and use of an innovation creates in an individual. Of all three dimensions, instrumental attributes are considered to be the most influential when it comes to the purchase of an EV. An explanation for this is that instrumental attributes and therefore usage related features of a car do not only influence the intention to adopt an EV but also how the other two dimensions are perceived by an individual. This behavior is also reflected in the model the authors apply to investigate their research hypotheses. In the analyses not only the influence of perceived instrumental attributes of EVS on the adoption intention of this vehicle type were investigated directly but also mediated through the other two dimensions. The results reveal a significant influence on EV adoption intention stemming from all motivational dimensions of consumer innovativeness and a mediation effect through the dimensions hedonic and symbolic motives.

The last study that is reviewed in this part addresses the issue functional limitations or instrumental attributes could have for the assessment of the innovativeness of an individual if it is solely based on the timeliness aspect of the adoption of a new technology. This specific study was carried out by Morton et al. (2016). The authors refer to the argument of Midgley and Dowling (1978) that people might be innovative but they are restrained to adopt a new technology because of for

example a lack of financial resources which inhibits them to be able to afford this technology. Consequently, Morton et al. (2016) considered two different types of innovativeness in their analyses which they measured through surveys. The first is termed innate innovativeness and should capture the individual's inherent desire to acquire innovations. The level of innate innovativeness of the survey participants is measured by evaluating specific psychological as well as sociological determinants. Innate innovativeness also influences the second type of innovativeness considered in the study, which is the actualised innovativeness. Actualised innovativeness in the study of Morton et al. (2016) is the visible innovativeness and is measured by asking the survey respondents whether they own or intend to own a set of products in the near future, which can be considered innovations as well. As pointed out previously, the relationship between innate and actualised innovativeness can be distorted by inhibiting factors such as financial constraints. The results of the analysis revealed that a higher level of innate innovativeness measured with the sociological determinants positively influence the actualised innovativeness. The actualised innovativeness, measured with not only the products that are owned but which are also desired to be owned in the near future, in turn positively influences the intention of an individual to adopt an EV.

Many limitations of the studies in the research stream of EA and the EV market also apply to the extant literature in the strand of research discussed above. To the best of my knowledge, all of the studies dealing with the investigation of the influence of innovativeness on EV purchase behavior employed surveys as a data collection method. Consequently, survey biases such as social desirability or sample selection could also have influenced the outcomes of these investigations. Using the social desirability as an example, Tellis et al. (2009) who carried out surveys in different countries have found that people tend to over-report innovative behavior. They arrived at this conclusion as 16% of the respondents have claimed to have seen, purchased or own a nonexistent product. Moreover, since almost all of the papers that have been reviewed analyse the effect personal innovativeness has on the purchase intention of an individual, there is a high likelihood that the attitude-action gap could inflate the significance of the psychological factor innovativeness for this market, due to over-reporting innovative behaviour and not engaging in the actual purchase of this vehicle type. As pointed out in the study of Morton et al. (2016), mediating factors could inhibit the adoption of an innovation by innovative individuals, although they have expressed a desire to do so. One such factor could

be financial constraints of the innovative individual, which makes an EV not affordable to this person as it presents a relatively expensive innovation. This is also in line with the low-cost/high-cost model that postulates that individuals tend to engage more in pro-environmental behaviors which do not involve high costs (Diekmann, 1992; Kollmuss and Agyeman, 2002). Hence a further validation of the findings using actual sales data could be beneficial. Another limitation of these studies is that they solely focused on investigating the influence of innovativeness of people on the adoption intention of EVs in the private sector and neglect the two other customer groups in this market, which are corporations and the government. Corporations are able to purchase EVs and make them available to their employees as company cars. In addition, governmental institutions such as the police might replace their fleet of ICCs with new EVs. Consequently, studying the relationship of this determinant and the EV market on a macroeconomic level by looking at country data might provide interesting new insights.

Altering the research scope to a macroeconomic level and employing a determinant that reflects a country's level of innovativeness, provides additional advantages. Not only does it allow conclusions about the influence of changing levels in the public's innovativeness on the adoption of EVs, but it also enables a determination as to whether an innovative environment could be a beneficial prerequisite for the diffusion of such a high cost technology. Using the TPB as a theoretical background, it can be argued that based on the subjective norms dimension, people in an innovative environment perceive a social pressure to behave more innovatively themselves. Therefore, innovative behavior becomes more of a social norm which could lead to an increase in EV adoption. Moreover, combining this with the concept of symbolic motives individuals are also able to display their innovativeness with the purchase of an EV and are thus able to actively present their innovativeness to their social environment, thereby establishing and maintaining a certain social status (Noppers et al., 2014, 2015; White and Sintov, 2017; He et al., 2018). Noppers et al. (2014) for example by conducting surveys and asking the participants whether it is important to them that an EV enhances their social status or more generally asking whether an EV enhances the social status of the driver, found out that the symbolic motive of an EV is indeed a factor that positively affects the purchase intention. This is due to the improved ability to present and improve the status which the purchase of such a vehicle type entails. Furthermore, the researchers have found that the higher the society values a sustainable inno-

vation, the more likely it is for an individual to purchase an EV because of status enhancing reasons. Maintaining social status can be assumed to be closely linked to social pressure, thus status seeking behavior could potentially influence innovative behavior, which in turn could result in the adoption of an EV. Another reason why an innovative environment could lead to more EV purchases is the possibility of enhanced conditions for owning an innovation. In case of EVs, an innovative environment could for example foster the EV infrastructure by installing more charging stations. Determining whether country innovativeness is a significant determinant of the EV market is of interest for different groups of practitioners. Inter alia, for manufacturers of such high-cost innovations it could present an additional factor to consider, where to initially launch such a product. If country innovativeness turns out to be a significant factor, a faster diffusion of this product can be expected in these markets since more people are willing to purchase such a technology in the first phases after market introduction. According to Plötz et al. (2014) this time after the launch is especially important for a new technology to establish itself in the market as it is critical for its long term success to gain traction with early adopters. With progressing time, companies are likely able to offer the innovations for lower prices due to advancements in research and development as well as economies of scale, reducing the risks of the individuals to purchase the new technology (cf. Kemp and Pearson, 2007). Thus, the attractiveness of this product also rises in less innovative countries as the population in these countries can, based on the DOI theory, be defined as more risk averse.

3.4.2.2 Research Hypotheses

Based on the identified gaps in the literature, three different research questions that will be investigated in Chapter 7 are developed. First of all, it is hypothesised that country innovativeness positively influences the EV market. This hypothesis is grounded on the findings of previous research focusing on personal innovativeness on an individual level as well as the various theories such as the concept of symbolic motives, DOI theory or TPB. Hence the null as well as alternative hypothesis that will initially be investigated in Chapter 7 can be defined as follows:

Hypothesis 3.2.

H₀: Innovativeness does not significantly and positively influence the EV market.

H_A: Innovativeness does significantly and positively influence the EV market.

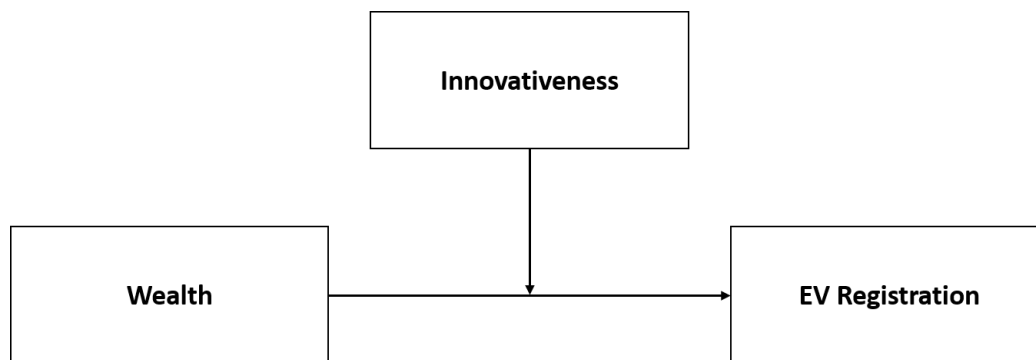
Innovativeness as a Moderator: In a second step, the significance of innovativeness as a moderator variable between wealth and EV registrations is analysed and therefore responds to the call of Al-Jundi et al. (2019) to investigate the relationship between wealth, innovativeness and the adoption of a new technology in a mediated regression setting. Although the authors hypothesise that wealth moderates the influence between innovativeness and the adoption of a new technology, it is assumed that the moderation effect between these variables is reversed for the EV market. Considering that EVs are a high-cost technology, a certain level of wealth is considered to be a requirement to be able to afford this product. A higher level of innovativeness increases the desire to possess such a technology but can only be fulfilled if the required condition of wealth is met. Consequently, it is argued that innovativeness positively amplifies the relationship between wealth and EV adoption and therefore functions as a moderator variable as depicted in Figure 3.13. The appropriate hypothesis can be defined as follows:

Hypothesis 3.3.

H_0 : *Innovativeness does not significantly and positively moderate the influence wealth exhibits on the EV market.*

H_A : *Innovativeness does significantly and positively moderate the influence wealth exhibits on the EV market.*

Figure 3.13: Innovativeness as a Moderator



Notes: Own illustration.

Innovativeness as a Mediator: On the opposite side, the findings of various research also allow the assumption of a possible mediating influence of innovativeness between wealth and the EV market. Amongst others, the studies of Shane (1993);

Dekimpe et al. (2000); Tellis et al. (2003) and Chandrasekaran and Tellis (2008) have shown a significant influence of the wealth of a country and its inhabitants on the general pace of the adoption of a new technology, which represents a country's level of innovativeness. The foundation of the argumentation of these articles lies in the DOI theory developed by Rogers (1962). In particular, as already discussed in Chapter 3.2.1.3, Rogers (2003) by establishing the DOI theory has found that wealthier people are usually more innovative, which can be traced back to the lower utility wealthier people receive from money, also known as the "wealth" effect (Tellis et al., 2003). As a consequence, wealthier people can better afford and are more prone to invest money into riskier projects, such as new products in their early stages (Dickerson and Gentry, 1983). Furthermore, as argued for the moderation effect, it is assumed that new products start at relatively high prices and then continuously drop in price, which makes them affordable primarily for wealthy people in the first phases after launch. The risk aspect can be confirmed when looking at the EV market. Early adopters of this technology were exposed to high initial risks such as a lack of charging infrastructure. Moreover, the purchasing prices of this vehicle type were significantly higher than for comparable ICCs in most countries.

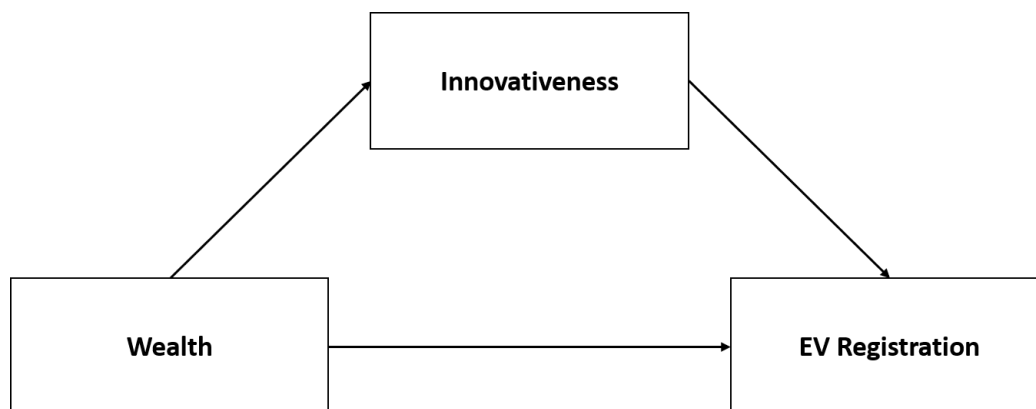
A study that has looked at other factors that could mediate the relationship between wealth and the EV market was carried out by Rietmann and Lieven (2019). Arguing that countries with higher purchasing powers are also more likely to be able to afford subsidies, favourable traffic regulations for EVs and investments into the charging infrastructure, uncovered a significant mediating influence of these determinants between purchasing power and EV adoption. However, to the best of my knowledge, no study has investigated the mediating effect of innovativeness between wealth and EV purchase behavior. Hence, in this study as a third research question, it is hypothesised that country innovativeness mediates the relationship between wealth and EV adoption. Thus, as illustrated in Figure 3.14 the wealth of a country and its inhabitants should not only directly but also indirectly foster the development of the EV market through a higher level of innovativeness of its citizens. The investigated hypothesis can therefore be defined as follows:

Hypothesis 3.4.

H_0 : Innovativeness does not significantly and positively mediate the influence of wealth on the EV market.

H_A : Innovativeness does significantly and positively mediate the influence of wealth on the EV market.

Figure 3.14: Innovativeness as a Mediator



Notes: Own illustration.

3.5 Subsidies and the Electric Vehicle Market

Subsidies are a policy measure that is applied by a multitude of governments to foster the development of the EV market. By using subsidies, governments try to encourage the adoption of EVs with incentives rather than by prohibiting the sale of other vehicle types. Thereby, these incentives can take on different forms but can broadly be categorised into financial and non-financial subsidies. Financial incentives can either directly influence the purchasing price of an EV in form of for example rebates or indirectly stimulate the attitude of an individual towards this vehicle type by reducing the operational costs of an EV by for example granting exemptions or reductions of taxes. Non financial incentives on the other side are supposed to convince a potential customer of this vehicle type by providing him or her with special rights such as a permission to use Bus lanes. In contrast to psychological determinants, there is already a well established research stream focusing on the relationship between subsidies and the EV market, also on macroeconomic level. However as the market is evolving quickly, it is important to frequently investigate whether the findings still hold. Moreover, as subsidies are determined

to be an important determinant and a policy measure to directly intervene in the market it makes sense to review extant literature and check whether they exhibit a potential lack of research. Consequently, in the following a few of the core studies in this research stream are reviewed to identify the status quo of research and assess the research gaps. Based on the findings of the review, a hypothesis will be developed in the subsequent chapter.

3.5.1 Extant Literature on the Influence of Subsidies on Electric Vehicle Purchase Behavior

As subsidies have been determined an important factor for the adoption of EVs by several researchers, as found out in the SLR, it is not surprising that literature reviews already exist that try to summarise the findings of extant research that particularly focus on this determinant. The importance of summarising the findings is further underscored by the different incentives that can be granted and the different effects exhibited depending on the geographical region in which they are granted (Münzel et al., 2019). Two excellent literature reviews have for example already been conducted by Hardman et al. (2017) and Hardman (2019). In the first review, Hardman et al. (2017) discuss the findings of previous literature that focused on the influence of purchase incentives for HEVs, PHEVs and BEVs and therefore limit their research scope to investigations on financial incentives. Based on the review, the authors come to the conclusion that incentives granted at the point of sales are the most effective. In the second review, Hardman (2019) looked at non-financial and recurring incentives, finding that these types of subsidies also exhibit a significant positive influence on the EV market. Criticising that in these reviews only a general discussion on the effectiveness of the subsidies on EV adoption behavior takes place but not a quantification of the actual marginal effects of these subsidies on the EV market, Münzel et al. (2019) executed a comprehensive review of previous research that investigated the influence of subsidies on the EV market by employing actual market data in their work. Consequently, the review carried out in their study corresponds with the scope of analysis of this dissertation, which is using actual market data to circumvent issues that might arise from the attitude-action gap as well as potential survey biases.

However, in the course of the SLR several studies were identified that had the same scope of analysis but do not appear in the list of studies of Münzel et al.

(2019). One reason for this is that some of the studies were first published after the work of Münzel et al. (2019). Consequently, it was decided to complement the list of studies identified by Münzel et al. (2019) and prepare a table of all the studies identified in the SLR that investigated somehow the influence of subsidies on the EV market by employing market data (see Table 3.5). However, in this review studies are not considered that focus on HEVs or due to the limitations set for the SLR which were not published in a peer reviewed journal or before the year 2010. Hence, there are some studies in the Table 3.5 that overlap and a few studies that supplement the work of Münzel et al. (2019). The studies that overlap for both overviews are highlighted with a check mark in the last column of the table. Moreover, following the structure of Münzel et al. (2019) columns that provide information about the considered vehicle type, geographical region, investigated time period, methodological approach as well as whether financial or non-financial incentives were investigated, are represented in the table. Hence, for a detailed discussion about differences between extant literature in regard to used statistical approaches, applied measurements for the dependent variable and thus the considered surrogate for the EV market as well as considered control variables this study refers to the study of Münzel et al. (2019).

Table 3.5: Econometric Studies Investigating the Influence of Subsidies on the EV market

Author	Vehicle Type	Geographic Region	Time Resolution	Method	FI	Non-FI	In Münzel et al. (2019)?
Sierzchula et al. (2014)	PEV	Global countries	2012, yearly	Cross sectional OLS	+		✓
Wesseling et al. (2015)	EV	Global car manufacturer data	2012	Mann-Whitney U Test			
Vergis and Chen (2015)	BEV, PHEV	US states	2013, yearly	Stepwise linear reg.	+	+	✓
Mersky et al. (2016)	BEV	Norwegian municipalities	2000-2013, yearly	Stepwise linear reg.	0	+	✓
Zhang et al. (2016b)	BEV	Norwegian municipalities	2011-2013, yearly	Random coefficient discrete choice model	0	0	
Zhang et al. (2016a)	EV	China, 88 pilot cities	2013-2015, yearly	Pooled OLS	+	+	
Wang et al. (2017a)	BEV, PHEV EV	Chinese cities	2013-2014, yearly	Stepwise linear reg.	0	0	✓
Li et al. (2017)	PEV	US metro areas	2011-2013, quarterly	FE panel data reg./ GMM	+		✓
Soltani-Sobh et al. (2017)	EV	US, 19 states	2003-2011, yearly	FE & RE panel data reg.	+/0	+/0	
Ma et al. (2017)	PEV	China, 6 cities	2011-2016, monthly	Panel co-integration	+	+	
Heidrich et al. (2017)	EV	UK, 30 cities	2015	Wilcoxon rank sum test/ Cross sectional OLS		+/-	
Sheldon and DeShazo (2017)	PEV	California, census tract	December 2013	Generalized propensity score		+	
Jenn et al. (2018)	PEV	US states	2010-2015, monthly	FE panel data reg. GMM with LDV	+/-	+/-	✓
Egnér and Trosvik (2018)	BEV	Sweden, Municipalities	2010-2016, yearly	FE panel data reg.		+/-	
Narassimhan and Johnson (2018)	PEV, BEV PHEV	US states	2008-2016, quarterly	FE panel data reg./ GMM with LDV	+/-	+/-	

Yan (2018)	BEV	28 European countries	2012-2014, yearly	FE panel data reg.	+		
Wee et al. (2018)	PEV, BEV PHEV	US states	2010-2015, semi-annual	FE panel data reg.	+	+/-	✓
Zambrano-Gutiérrez et al. (2018)	PEV	US states	2010-2016, yearly	FE panel data reg.	+/0	-	
Zhou and Li (2018)	PEV	US metro areas	2011-2013, quarterly	FE panel data reg.	+	+/-	
Wang et al. (2019)	BEV, PHEV	Global countries	2015	Cross sectional OLS	0	+/0	
Rietmann and Lieven (2019)	PEV	20 Global countries	2017	Covariance-based SEM	+	+	
Münzel et al. (2019)	PEV	32 European countries	2010-2017, yearly	FE panel data reg.	+		✓
Qiu et al. (2019)	EV	China, 88 pilot cities	2014-2015, monthly	RE panel data reg./ GMM with LDV	+	-/0	
Li et al. (2019)	EV	China, 43 cities	2011-2017, yearly	Pooled OLS	+	+	
Clinton and Steinberg (2019)	BEV	US states	2010-2014, quarterly	FE panel data reg.	+		✓
Kim and Heo (2019)	PEV	Korea, 16 metro municipalities	2013-2017, yearly	Negative binomial reg.	+		

Note: Categories are based on Münzel et al. (2019) and therefore partially overlaps.

FI = Financial Incentives

PEV = Cumulated BEV & PHEV data.

EV = Not clearly defined in paper.

+ = positive relationship, - = negative relationship, +/- = inconclusive relationship, 0 = insignificant, n.r. = not reported

The pioneering study in this strand of research that looked at the influence of subsidies on the EV market by employing actual market data was performed by Sierzychula et al. (2014). Focusing their research endeavours on the registration rate of EVs in the year 2012 across 30 countries, the researchers found that next to the charging infrastructure as well as whether a country was host to a global EV producer, financial incentives is the only determinant that positively influences the EV market. In particular, the results of the analysis suggest that a 1,000 € increase in subsidies would result in a 0.6% increase in the registration rate of EVs. Considering that the investigation focuses on one of the early years after this vehicle type was introduced to the mainstream market, the choice of a cross-sectional OLS that solely relies on between country differences seems reasonable as not many observations over time for this vehicle type were available. However, it should be noted that it is difficult to capture all country specific differences between the sample countries that could influence the EV market in a single model, wherefore statistical approaches that base their approximations on between unit differences might bias the estimates. To account for such cross regional differences later studies (e.g. Li et al., 2017; Soltani-Sobh et al., 2017; Jenn et al., 2018) in this research field were able, with an increasing number of observations over time, to apply panel data regression models and in particular within estimators as reflected in Table 3.5.

Amongst others, Clinton and Steinberg (2019) applied a fixed effects (FE) panel data regression to analyse the influence of financial incentives on BEVs in their investigation. Using quarterly observations for the time period 2010 to 2014 and covering the US states as a geographic region, the researchers have found a significant and positive relationship between financial incentives and the registrations of BEVs per capita. Based on the results obtained in the regressions an increase of US \$1000 in subsidies would lead to an increase of approximately 7.5% registered BEVs per capita. Although, a comparison of the approximated effect with the one obtained from Sierzychula et al. (2014) is difficult and limited as the considered determinant in this study only considers BEVs and is put in relationship on a per capita and not to the total amount of car registrations, the estimates in the study of Clinton and Steinberg (2019) imply a stronger influence of subsidies on the BEV market. In addition to the analysis of the accumulated amount of incentives, the authors performed regressions on a more detailed level for the granted subsidies in the US by distinguishing between rebates and tax credits. In doing so, Clinton

and Steinberg (2019) found out that while rebates exhibit a significant and positive influence on the BEV market, granted tax credits are not a significant determinant.

Another interesting study that relied on an FE approach was executed by Wee et al. (2018). In their study, a focus was also laid on US states covering the time period between 2010 and 2015 with semi-annual observations. Moreover, similar to Clinton and Steinberg (2019), the authors applied a three dimensional FE model consisting of country, year and EV model fixed effects. However, different to the study of Clinton and Steinberg (2019), Wee et al. (2018) did not only analysed the influence of subsidies on BEV registrations but also on the registrations of PHEVs. The researchers hypothesise a different influence of subsidies on each vehicle type since they claim that there are important differences between BEVs and PHEVs which could lead to a different valuation of subsidies for the purchase decisions. Analysing BEVs and PHEVs combined in an FE regression, the outcomes of the investigation suggest that a US\$1,000 increase in subsidies results in an increase of approximately 7.5% new registrations of EVs. Distinguishing between BEVs and PHEVs, it was found that while a US\$1,000 increase in subsidies would lead to an increase in registrations of approximately 10.5% for BEVs, the increase in registration is lower for PHEVs with only about 5.2%. Similar results for the different influence of subsidies depending on the vehicle type were found by Narassimhan and Johnson (2018). The researchers found that financial incentives more strongly impact BEVs compared to PHEVs and in some cases subsidies do not even exhibit a significant influence on PHEV sales per capita. Going one step further, the authors even discovered differences in the impact of subsidies within a vehicle type. For example while a significant influence for the tax credit was detected for the lower cost BEV no significant influence was uncovered for the higher cost BEV considered in the study. Conversely, in the case of tax waivers the influence was insignificant for the lower cost BEV and significant for the higher cost version. According to the results of the study, rebates exhibit a significant influence on both car categories. In addition to analysing potential differences depending on the vehicle type, this study also applied next to the FE approached another statistical method in form of a generalized method of moments (GMM). This approach is required due to the inclusion of a lagged dependent variable and the subsequent endogeneity issue that arises from including a lag of the dependent variable into the regression. However as argued by the authors, the inclusion of a lagged dependent variable might be important to account for the natural diffusion

of a new technology. Therefore, excluding this factor could lead to biased results in form of overestimating the actual impact of subsidies on the market. Including a lagged dependent variable in the regression into the analysis and applying a GMM approach, the estimates of the subsidies variables are as hypothesised by the authors smaller in magnitude than approximated by the FE model. This suggests that an FE approach could have overestimated the influence of subsidies on the BEV and PHEV market. Support for the criticism on the FE approach in this research stream can also be found in Jenn et al. (2018). Being an advocate for the inclusion of a lagged dependent variable to account for the exponential growth of an innovation and therefore the application of an instrumental variable approach, one of the authors has already proven in an earlier study focusing on the HEV market, that neglecting the influence of the natural diffusion of a new technology could lead to an overestimation of the influence of subsidies (Jenn et al., 2013). In the recent study of Jenn et al. (2018), when comparing the estimates obtained with the FE approach with those obtained from the GMM approach, the results indicate that neglecting the exponential growth in the case of EVs in the US also leads to an overestimation of the influence of subsidies. The approximated impact of a US\$1,000 increase in tax credits on the EV market ranges from 0.891% based on the model including a lag of the dependent variable to 4.41% for the model without a lag of the dependent variable.

What is striking in most of the research is that it is strongly US and China centered. Only two studies were uncovered in the SLR that took on a European focus, not considering the studies that focus on a European country on a national level. A differentiation between investigations on national and international level should be made, as the considered taxes depend on it. For example, it would not make sense to include taxes that apply in an entire country in an investigation on national level, as all regions within a country receive this benefit. The earlier of the two studies was performed by Yan (2018) and focuses on the influence of tax incentives on the registration rate of BEVs for 28 European countries covering the time period between 2012 to 2014. The authors calculated tax incentives for 10 different BEV models from different car segments, thereby creating a three dimensional panel data consisting of country, year and model. The results of an FE analysis indicate that a 10% increase in tax incentives would result in an increase of about 3% in the registration rate of BEVs. Building on this study, Münzel et al. (2019) in their study extended the geographic scope of analysis by four countries as

well as collected subsidy data for the years 2010 to 2017. Another difference in the data collection process was that they did not only consider BEVs but also PHEVs in their investigation and used an aggregate of the registration rate for the dependent variable and an average of the granted subsidies for one BEV and one PHEV model as the independent variable. The findings of the study show that a 1,000€ increase in the amount of granted subsidies should lead to a 5 to 7% increase in the registration rate of EVs. When comparing this estimate with the one obtained from Yan (2018), this could suggest that the influence of subsidies might change over the years. Furthermore, Münzel et al. (2019) in a later step of their analysis distinguish between one time subsidies and recurring subsidies. Interestingly, the authors have found a much stronger effect stemming from recurring incentives on the registration rate of EVs than from one time subsidies. Going one step further in their investigation, an analysis of the individual one time subsidies on the registration rate of EVs revealed that rebates, taxes granted at the point of sales as well as income taxes exhibit a significant influence. The coefficient for the estimate of income taxes, however, showed a negative sign implying a negative relationship to registration rate of EVs. The authors argue that this negative sign could be caused by the small number of observations for this variable.

Based on the literature reviewed above, it can be seen that in contrast to the determinants EA and innovativeness, an extensive body of literature already exists that analysed the influence of subsidies on the EV market by employing actual market data. Nevertheless, different gaps can also be identified in this research stream. Starting with the geographic focus of previous research, a lack of research is determined for analyses on the European region. Considering that the granted subsidies differ in terms of design and amount depending on the country, the influence of financial incentives might differ based on the region. Moreover, it can be assumed that customers of this vehicle type perceive subsidies differently because of behavioral differences. The two studies focusing on the European region provide interesting insights about the influence of subsidies on the registration rate of EVs, however, leave room for further research. First, considering the investigated time period, with studies focusing on the years 2012 to 2014 (Yan, 2018) and 2010 to 2017 (Münzel et al., 2019), the approximated effect of incentives on EV sales might have already changed. EVs are a relatively new technology, wherefore advancements in research and development make them cheaper each year. For example while as found out in a recent Bloomberg study a battery pack costed

more than US\$1,000 in 2010, the costs are currently approaching the US\$100 mark, making EVs as expensive as gasoline fueled cars (Boudway, 2020). Hence, it could be assumed that subsidies as a means of making EV prices competitive to ICCs lose in importance. Consequently, it makes sense to frequently repeat studies as recommended by (Block and Kuckertz, 2018; Camerer et al., 2018), especially for such a new technology to test whether relationships still hold. Indications of changes in the magnitude in the relationship between subsidies and the EV market can as previously discussed already be found when comparing the results of Yan (2018) with those of Münzel et al. (2019). Not as important as the previously mentioned reason why investigating the influence of subsidies on the EV market in the European region could be beneficial with more recent data, is the increased number of observations which could make the standard errors of the estimates more robust. This is also recommended by Münzel et al. (2019).

Looking at the more recent study of the two, the study of Münzel et al. (2019) exhibits new methodological avenues that should be applied to verify the obtained results. As previously discussed, several researchers included a lag of the dependent variable to account for the exponential growth and natural diffusion of this technology. They have shown that the omission of this effect could lead to an overestimation of the estimated impact of subsidies. Thus, it should be tested whether the inclusion of a lagged dependent variable in the analysis and hence the application of an instrument variable approach such as a GMM leads to different results for the determinant subsidies compared to when using an FE approach. Another potential for further research that is based on the work of Münzel et al. (2019) arises from the aggregation of BEV and PHEV sales data and the averaging of the subsidies for these vehicle types. In the literature review it has been pointed out that subsidies might affect the vehicle types differently. Therefore an interesting contribution could be to also differentiate between BEVs and PHEVs.

3.5.2 Research Hypothesis

Based on the identified gap in the literature, Chapter 8 in this dissertation deals with the question whether subsidies issued in European countries significantly influence the adoption of EVs in this region. Considering, the results of extant research, a positive influence stemming from subsidies on the EV market is hypothesised. Consequently, the null as well as alternative hypothesis can be defined as follows:

Hypothesis 3.5.

H₀: Subsidies do not significantly and positively influence the EV market.

H_A: Subsidies do significantly and positively influence the EV market.

In addition to trying to answer this general research question, different nuances will be made to address the possible shortcomings of the study of Münzel et al. (2019). Hence, an attempt is made to answer the sub-questions that arose from the last part of the literature review. Therefore, this research is also determined to find out whether neglecting a lagged dependent variable leads to an overestimation of subsidies. Moreover, by distinguishing between BEVs and PHEVs, differences in the influences of subsidies are investigated based on the vehicle type. Recalling the results of previous studies looking at different geographic regions, it is hypothesised that the influence of subsidies on BEVs is stronger than on PHEVs. Lastly based on the advancements in the technology and the resulting decreases in prices, it is assumed that the magnitude of the influence of subsidies decreased in the last years.

RESEARCH PHILOSOPHY & DATA

This chapter is dedicated to providing information about the research philosophy and data of this thesis. Before a detailed explanation of the considered data and their corresponding sources takes place, the underlying research philosophy for this thesis needs to be briefly outlined. The research philosophy is presented prior to the discussion of the data as an individual's philosophy of conducting research does not only influence the applied methodological approaches but also the sources and characteristics of the analysed information.

4.1 Research Philosophy

Research can be defined as the development of knowledge (Saunders et al., 2009). Knowledge which is developed through the output of a research process is implicitly influenced by a set of assumptions made by the researcher. This set of assumptions includes assumptions about the nature of reality, theory and the significance of empirical analysis and represents the research philosophy of an individual researcher (Ryan et al., 1992). In the following, the *positivist* research philosophy, which is the philosophical approach relied on throughout this investigation, is presented. Thereby, a brief explanation of this research philosophy takes place, followed by an outline of the positivist research process and the influence of this philosophy on the output and interpretation of results.

4.1.1 Positivism

Positivism is one of the most commonly underlying research philosophies in finance research (O'Connor, 2015). From a positivist's point of view the reality is considered stable and can be viewed objectively. This in turn means that relationships can and should be analysed with no interaction between the researcher and the phenomena of interest. Hence under the positivist paradigm, the reality is seen to be fragmented in different variables and processes which are all independent from each other. This allows to study the distinct variables and processes separately. Finally, the composition of all variables and processes represent the single and tangible reality (Guba and Lincoln, 1982).

The objection to the interaction between the researcher and the studied phenomena characteristic to the positivist school of thought is also reflected by the criticism raised in the literature review. In the literature review it was pointed out that by conducting surveys the researcher interacts with the survey respondents which could result in potential biases such as social desirability or leading bias. These biases can compromise the collected data and thus prevent an objective observance of the phenomena. Consequently, as later discussed in the data section, in this research more objective measurements of the variables that do not require an interaction with the studied phenomena are employed.

4.1.2 Positivist Research Process

One of the basic assumptions of positivist research is that a true reality exists which is external to and unaffected by the researcher's personal values, convictions or expectations. This reality can be observed through objectively measurable facts, wherefore positivism typically takes a deductive approach and puts an emphasis on objective variables which are not subject to potential influences of research participant's personal beliefs or values. The aim of objectivity under this research philosophy further encourages quantitative methods of research as these are less subject to the researcher's personal interpretation (Saunders et al., 2009; Park et al., 2020). Consequently, this implies that when two researchers investigate the same phenomenon, they should arrive at the same conclusion, if both carried out the research correctly (Blumberg et al., 2008; O'Connor, 2015).

4.1.3 Positivist Research Output and Interpretation

Due to the objectivity in the research process, causal relationships between variables and processes can be identified which are considered generalisable. Generalisability implies that the findings obtained from a sample in the course of a research are transferable and allow to make inferences about the entire population (Vigne, 2017). Based on the generalisability of the causal relationship, a contribution of the knowledge development under this paradigm is that predictions about the future can be made (Saunders et al., 2009). Besides generalisability, O'Connor (2015) points out that there are two further criteria that assess the usefulness of the obtained results under a positivist paradigm, namely reliability and validity.

The reliability of a result can also be understood as its consistency. This means that the results of a research must be the same or only insignificantly deviate if the research is repeated, regardless of location and time (Sekaran and Bougie, 2009). To obtain reliable results in a research setting, methodologies have to be applied that provide the most accurate results (Gujarati and Porter, 2009).

On the other side, the validity assesses the quality of a research output regarding the accuracy of the applied measures. It therefore evaluates to what extent the results obtained from the applied test procedures allow inferences on the relationship of interest. Hence, it assesses the appropriateness, meaningfulness and usefulness of the results (O'Connor, 2015). It can further be distinguished between internal and external validity. While internal validity is concerned with the design and implementation of the applied testing procedures and evaluates their respective appropriateness, external validity focuses on the generalisability aspect of a research and questions whether the results are transferable to the entire population (Aliyu et al., 2014; Helbing, 2019).

4.2 Data

In this section the data considered throughout this thesis is presented. Thereby, the selection of the specific data is justified as well as references to the sources are made. All data is collected for 29 countries, namely: Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Kingdom. Hence, the data set consists of 27 EU and 2 EFTA member states.

The decision to collect data for these countries is based on the identified lack of research for this region. Furthermore, the reason why such a wide geographic region is considered and no focus is laid on a single or a few countries is based on the fact that only a few observations over time exist due to the relatively recent introduction of EVs to the mainstream market and the low frequency of the data. Data is almost exclusively available on an annual basis, which also determines the observation frequency of the final data set. Hence, following previous literature it has been decided to collect data for different countries over time and thus obtain a data set in form of a panel.

In the following, the choice of the data sources for the three main independent variables EA, innovativeness and subsidies is initially justified and described in detail. Thereafter, the most appropriate selection for the dependent variable and determinants that function as control variables is discussed. In the same part the sources where the data for these determinants are obtained from is presented. In the last part of the chapter, other important properties of the determinants are discussed that have influences on the consideration in the respective analyses.

4.2.1 Environmental Awareness

Twitter: The first measurement of EA applied in this investigation significantly differs from previous studies in this field of research discussed in Chapter 3.4.1.3 of the literature review. While the usual technique to determine an individual's level of EA, is to carry out surveys a more unbiased approach in form of a Twitter keyword analysis is applied in this research. A keyword analysis entails the use of certain words that can function as search terms surrogating for the analysed topic. The choice of the keywords in this study was restricted to two word pairs, namely *climate change* and *global warming*, as it was decided to use an existing database rather than actively collecting the tweets. The decision was based on the fact that when tweets are deleted they are no longer accessible for analysis. Using a database established closer to the analysed time frame therefore provides the possibility to obtain a more accurate picture of the public's interest in this topic at the respective point in time, as fewer tweets have been deleted. Access to a database of tweet IDs that includes all Tweets with the terms *climate change* and *global warming* published from 2007 to 2017, collected by Samantray and Pin (2019), was obtained from the Harvard Dataverse. Consequently, all tweets that mention these word pairs in text or in form of a hashtag were considered in this study.

The applied search terms are also in line with previous studies employing Twitter or other social media platforms to analyse environmental issues (e.g. Kirilenko and Stepchenkova, 2014; Kirilenko et al., 2015; Veltri and Atanasova, 2017; Santi, 2021). While other terms may be used in tweets relating to environmental topics, it is believed that adding further terms would not significantly impact the findings as it can be expected that the general trend would remain the same. A distinction between positive and negative statements was not made, since in this study it is assumed that negative statements can also be seen to indicate the relevance of this topic for people as they might trigger educational conversations. In total, Samantray and Pin (2019) collected 14,353,859 tweets between 2007 and 2017. 13,671,284 of those fell into the investigated time horizon of this study.

Due to data process restrictions put in place by Twitter, it was decided to neglect the usage of a Twitter API on a data analytic software and to count the number of tweets within a year by interpolation. This is possible as tweet IDs contain a timestamp component. More recent tweet IDs have a higher value than older tweet IDs. By organising tweet IDs in ascending order, I was able to determine the first and last tweet within a year. Subsequently, all tweets between the first and last tweet of a year can be counted into the corresponding year. The used data does not violate any ethical standards, as no tweet content is being published or evaluated. The final measurement of EA was in form of a ratio, whereby the amount of tweets using these search terms in one year was put into relation to the number of active Twitter users in the corresponding year.

Google Trends: To validate the findings of the regression employing Twitter as a data source for EA, a second measurement of EA in form of a Google Trends (GT) analysis is applied. GT is not an uncommon measure for awareness in this strand of literature. Vergis and Chen (2015) for example used GT to measure a society's awareness of EVs. Google Trends measures the search frequencies of the search terms based on an index. The highest value of this index is 100 and represents the month with the highest popularity of the search term. The annual value has been calculated using the average of the 12 months' values. The applied search term to measure EA in GT is *climate change* in the corresponding languages of the countries. In some cases, when the search term *climate change* was not used frequently enough in one language, the translation of *global warming* in the domestic language was used instead. Two different languages were used for

Belgium and Switzerland as there is no single main language spoken in these countries. The Italian language has not been considered for Switzerland in this investigation, as the term *cambiamento climatico* was not used frequently as a search term in this country. Table 4.1 presents the applied search term for each country and the corresponding English translation.

Table 4.1: Search Terms Google Trends

Country	Search Term	English Translation
Austria	Klimawandel	Climate Change
Belgium	Klimawandel & Réchauffement Climatique	Climate Change
Bulgaria	глобално затопляне	Global Warming
Cyprus	κλιματική αλλαγή	Climate Change
Czech Republic	změna klimatu	Climate Change
Denmark	global opvarmning	Global Warming
Estonia	globaalne soojenemine	Global Warming
Finland	ilmastonmuutos	Climate Change
France	Réchauffement Climatique	Climate Change
Germany	Klimawandel	Climate Change
Greece	κλιματική αλλαγή	Climate Change
Hungary	éghajlatváltozás	Climate Change
Ireland	Climate Change	Climate Change
Italy	cambiamento climatico	Climate Change
Latvia	globālā sasilšana	Global Warming
Lithuania	klimate kaita	Climate Change
Luxembourg	Réchauffement Climatique	Climate Change
Malta	Climate Change	Climate Change
Netherlands	klimaatverandering	Climate Change
Norway	global oppvarming	Global Warming
Poland	zmiana klimatu	Climate Change
Portugal	das Alterações Climáticas	Climate Change
Romania	schimbarea climei	Climate Change
Slovakia	globálne otepľovanie	Global Warming
Slovenia	globalno segrevanje	Global Warming
Spain	cambio climático	Climate Change
Sweden	klimatförändring	Climate Change
Switzerland	Klimawandel & Réchauffement Climatique	Climate Change
United Kingdom	Climate Change	Climate Change

Note: Google Trends measures the search frequencies of the search terms based on an index. The highest value of this index is 100 and represents the month with the highest popularity of the search term. The annual value has been calculated using the average of the 12 months values. Two different languages were used for Belgium and Switzerland as there is no single main language spoken in these countries. The Italian language has not been considered for Switzerland in this investigation, as the term *cambiamento climatico* was not used frequently as a search term in this country.

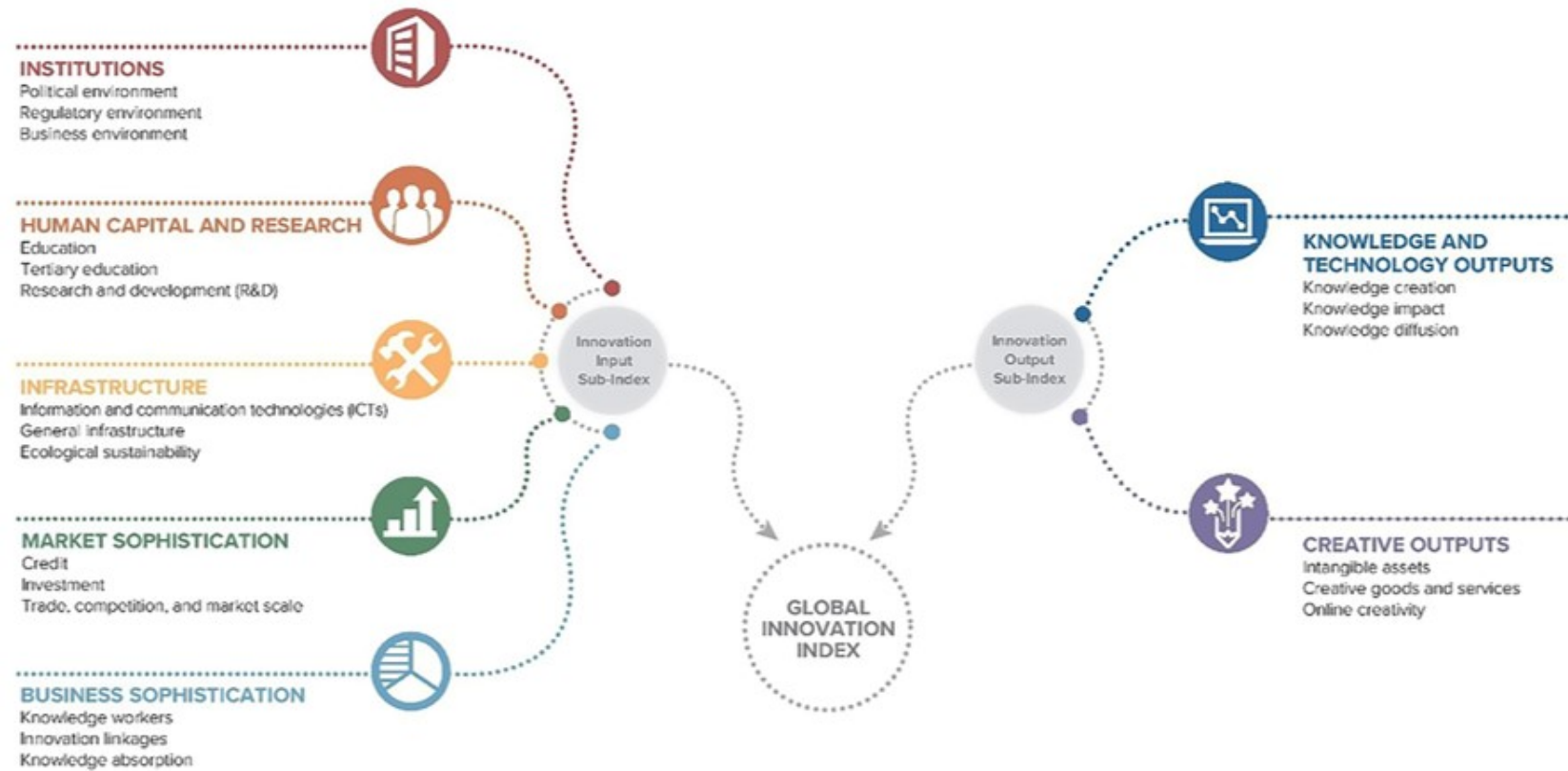
4.2.2 Country Innovativeness

Global Innovation Index: One of the key decisions for the study focusing on the influence of innovativeness on the EV market is to select an adequate measure of country innovativeness. Therefore, three requirements are established which an eligible method to measure innovativeness has to comply with. First of all, the method should include indicators reflecting the innovativeness of the population as well as companies and the government of a country, since these represent the potential customer groups of EVs. Furthermore, it should encompass measures reflecting country characteristics that could foster an innovative environment. Finally, the chosen index needs to be available for a time period that includes the first years that EVs were introduced to the general market. The index that met all of these requirements and is therefore considered the most suitable for this study is the Global Innovation Index (GII) published by Cornell University et al.

(2019b). The GII is a comprehensive index encompassing several indicators for population, company and government innovativeness as well as different measures of country characteristics conducive to innovation. In particular, the GII framework is structured as depicted in Figure 4.1. The final GII score, which can range between 0 and 100, that is assigned to a country depends on an Innovation Input Sub-Index and an Innovation Output Sub-Index. While the Innovation Input Sub-Index evaluates the prerequisites of an economy to enable innovation, the Innovation Output Sub-Index aims to measure the results of innovative activities (Cornell University et al., 2019a). Dividing innovativeness into input and output is similar to the differentiation of innovativeness made by Morton et al. (2016) as discussed in the literature review. The Innovation Input Sub-Index in this regard would resemble Morton et al.'s (2016) innate innovativeness, while the Innovation Output Sub-Index would reflect the dimension of actualised innovativeness. Hence, the measurement of innovativeness applied by the GII framework incorporates more than one dimension as recommended by Midgley and Dowling (1978) and Morton et al. (2016). Although more pillars influence the input sub-index than the output index, as it can be seen in Figure 4.1, both are equally weighted in the final estimation of the GII score.

Focusing on the individual pillars that influence the input index, it can be seen that they reflect the previously mentioned innovativeness measures for the citizens, companies and government of a country as well as evaluate how supportive the environment is for innovations. Looking at the human capital pillar as an example, by considering education, the measure also incorporates the characteristics of innovative individuals identified by Rogers (1962) DOI theory. Hence, as this measurement does not only meet the previously defined requirements but also incorporates the findings of innovation theories, it is considered to be an appropriate surrogate for country innovativeness in this study.

Figure 4.1: GII Framework



Notes: Illustration by Cornell University et al. (2020).

4.2.3 Subsidies

Subsidies issued by governments strongly deviate in definition, magnitude and applicability for EVs not only across countries but also between regions within countries. Broadly it can be differentiated between two types of subsidies, which are monetary and non-monetary incentives. While monetary incentives aim to reduce the total cost of ownership of this vehicle type, non-monetary incentives improve the convenience of owning this vehicle type. This is achieved by granting special permissions to EV owners such as using Bus lanes and access to restricted traffic zones, which owners of traditional ICCs do not receive. The latter category of incentives is not considered in this analysis as these types of incentives are normally granted on lower regional level and not on country level. Thus, differences of this subsidy type even exist within a country. Monetary incentives can further be divided based on the frequency in which they are granted. While some subsidies are only granted once, customers of EVs also receive repeated monetary benefits in several countries. Hence, this study also distinguishes between one time and recurring subsidies.

The predominant data source, where information about subsidies in the 29 countries considered in this investigation, is obtained from, is the European Automobile Manufacturers Association (ACEA) and in particular the tax guide published by this institution. In the tax guide, which is published annually, ACEA with the help of member associations from various countries including amongst others multiple countries in the EU and EFTA, summarises a comprehensive list of motor vehicle taxation in these countries. Going through all tax guides from 2010 to 2020 for this investigation, all incentives that explicitly provide beneficial treatments for EVs or which are based on CO_2 emissions, which is one of the greatest advantages of an EV, are documented and calculated. In the course of this process, one-time subsidies are further categorised into the subcategories *Point of Sales Tax reductions (POSTax)*, *VAT exemptions or reductions (VAT)* and *Income Tax reductions (IncomeTax)*. In the category Recurring Subsidies it has been distinguished between *Circulation Tax reductions* and *Company Car Tax reductions*. To supplement and cross check the incentives identified in the tax guide, different sources were consulted such as European Commission (2021) or e-mobility platforms. Encountering the issue that homepages are frequently updated, wherefore older information might not be available anymore, the internet archive has been utilised. A list of additional sources for the determination of subsidies can be found in Table 4.2.

To investigate the influence of monetary incentives on the EV market, different approaches have been applied in previous literature. Vergis and Chen (2015) in their study for example, utilised dummy variables to indicate whether a state granted a financial incentive or not. Based on this approach the researchers are able to analyse differences between these two types of states. However, they were not able to quantify the influence of a Dollar increase on the EV market. Since it can be assumed that the magnitude of subsidies strongly deviates between the countries in the European region, it makes sense to calculate the monetary amount of subsidies granted for the purchase of an EV in a country. Moreover, this approach allows to quantify the marginal effects on the market.

As previously discussed, subsidies differ based on the complexity of how they are defined by a government. While monetary subsidies such as rebates are easy to quantify because they are flat, policy incentives that are variable because they depend on vehicle attributes are more cumbersome to approximate. To calculate such incentives, two methods can be employed. The first method is to only rely on the car properties of an EV and calculate the difference of the costs of the tax with and without the incentive. The difference between the original price and the price with the applied incentive therefore represents the calculated amount of subsidies a country grants the consumer for the purchase of an EV. This approach is, however, exposed to one important issue. Several countries grant incentives that indirectly favor the purchase of an EV when comparing to an ICC, such as determining a tax amount based on CO_2 emissions. To calculate the amount of incentives, a reference value is required to which the CO_2 emissions of an EV can be compared, thereby facilitating an indirect inference of the amount of subsidies. An appropriate reference for this purpose could be to use the car properties of an ICC. This, however leads to an inconsistent approximation of the incentive amount, as the calculation methods are mixed. In particular, while some incentives would be calculated in relation to the original price other subsidies would be based on the advantage a tax incentive provides in comparison to a comparable ICC. Furthermore, in this investigation the focus is based on how ICC customers become EV customers. Therefore, it is assumed that subsidies are only perceived as such when they also provide advantages in comparison to ICCs. Consequently, to determine the amount of granted subsidies, this study follows the approach of Sierzchula et al. (2014), which has also been applied by Münzel et al. (2019), as it is considered to be the superior and more consistent approach of the two. Thus, subsidies are determined

based on differences in the tax amount between a BEV and PHEV on the one hand and their respective ICC counterpart on the other hand. Consequently, a crucial decision is to determine which BEV and PHEV as well as ICC models are used to approximate the subsidy amount granted to these vehicle types, since the car properties of the selected models have an influence on the calculated values. To avoid a subjective influence and ensure the comparability of results, as the investigation in Chapter 8 can be considered as an extension of the work of Münzel et al. (2019), the same models used in their studies are considered in this research. This means that the Nissan Leaf is selected to represent the BEV market and the Mitsubishi Outlander PHEV is the surrogate vehicle for the PHEV market. These cars were selected by the researchers as they exhibited a high market share and thus are considered to represent the BEV and PHEV market, respectively. In addition, the prices of the vehicles are not too high, making them a more viable alternative to the broader population. The comparability for the respective ICC counterparts is ensured based on performance measures of the engines as well as the vehicle classes. Taking also into consideration the high market share as well as data availability for the car properties, the models VW Golf VII 1.2 TSI and VW Tiguan 2.0 TSI are selected as the BEV and PHEV counterpart.

Since no exact way of measuring subsidies exists, in some cases the calculated amount of subsidies is subject to various assumptions made by the researcher. To reduce the influence of subjective biases to a minimum, this research follows the study of Münzel et al. (2019) regarding their approach of addressing the different issues. First of all, since several taxes depend on the vehicle price and these prices differ in the countries, the net prices for these four vehicles have to be approximated for the sample countries for the considered years. For this purpose, a car price index was developed. The first step to establish this index was to calculate the average net vehicle price of the VW Golf index, that has been reported by the European Commission (2007, 2008, 2009a, 2010a, 2011), for each country for the years 2007 to 2011. The reason why later years were not considered for this investigation is because the European Commission discontinued reporting the VW Golf index after the year 2011. In a second step, the average prices of the VW Golf index for the countries are put in relation to the value of a reference country, which provided easily accessible data for the four car models previously mentioned. The reference country in this case is Germany. Hence, the final index provides information about the net purchase prices of cars in the countries in relation to those in Germany.

Collecting price data for the BEV, PHEV and the two ICC models for Germany therefore allowed to approximate the net purchase prices for the other countries as well.

In the course of the vehicle price calculation further assumptions had to be made as different problems were encountered. One problem was for example that the production of the car model Nissan Leaf with its initial model specifications was stopped in 2018. Hence the price of the car needed to be approximated using a different but comparable EV car model. For this purpose the Renault Zoe with its basic equipment was used, which was available starting from 2013, as it is a comparable vehicle type. Moreover the price development of this BEV was similar to the Nissan Leaf in previous years. Hence, based on the development of the price of this vehicle, an approximation of how the price of the Nissan Leaf would have developed was made. Vehicle price approximations also had to be made for the VW Tiguan in the final year, since the Trendline model was no longer being produced. To nevertheless account for the development of the vehicle price, the price of the Trendline model was approximated by adding the price difference of the Comfortline model from the years 2020 and 2019 to the net purchasing price of the 2019 Trendline model.

A further issue that should be discussed is how subsidies granted for different customer groups is handled in this dissertation. Going through the ACEA tax guides, it can be noticed that some countries treat corporate and private customers differently in the determination of the taxable amount by granting different subsidies to them. Hence, the question arises how to handle subsidies that might only be granted to one customer group. In this research it has been decided to weight private and corporate incentives equally and consider them in their total amount in the calculation of subsidies. This decision is based on two reasons. First of all, no registration data is available that allows to distinguish between corporate and private purchasers of EVs. The second reason is, that it can be assumed that the incentives a corporation receives for purchasing an EV is passed on in the secondary market to private customers. Consequently, private customers also profit from the incentives granted to corporations.

The next problem that was encountered in the data collection was to decide how to deal with taxes that differ based on whether the car is registered for the first time or in case it is a second hand car. Considering the relatively recent introduction of this vehicle type to the mainstream market and that no well developed second

hand EV market exists (Wappelhorst, 2021), it can be concluded that the majority of the registered EVs are new. Therefore, it has been decided to use the calculation for cars that are registered the first time if differences exist. Another assumption that had to be made was in regard to the holding period of an EV for the calculation of recurring subsidies. In this investigation the holding period is reduced to one year. Thus, recurring incentives are calculated as one time subsidies. The reason for only considering one year as holding period is that no information about the actual holding period for EVs is available and it most likely differs between private and corporate customers. Reducing the holding period to one year at least allows the calculation of a consistent coefficient with one time subsidies.

Finally, to obtain the quantified incentives for the aggregated EV market, the calculated incentives for the BEV and PHEV vehicle were averaged. In the few cases where subsidies are negative, incentive values have been modified to 0. The rationale behind this data cleaning process is that negative incentives do not provide a benefit for the purchase of an EV, wherefore it can be assumed that they are neglected by the customers.

4.2.4 Dependent & Control Variables

EV registration rate: The dependent variable in this study is the ratio of EV registration figures to the total number of the new registrations in the automobile sector. Registration figures for BEVs and PHEVs of the M1 car category (passenger cars) were collected from the European Alternative Fuel Observatory (EAFO) (European Commission, 2021). EAFO is a highly reliable source as it receives data directly from the ministries of the respective countries. The decision to select registration figures instead of actual sales figures is twofold. First, there are more reliable sources for the registration of EVs available as these values are mostly measured by state agencies. The second and more important reason behind the choice is that this figure is more likely to represent where cars are actually used, as vehicles can potentially have been bought in foreign countries. Values for BEVs and PHEVs were collected separately and then aggregated, representing the numerator of the ratio. These figures are then put in relation to the total number of passenger car registrations in the corresponding year and country, which data was obtained from ACEA (2021). The rationale behind using registration shares instead of total registration numbers, is because of the different sizes of the car markets of the countries. Furthermore, a positive side effect of using a ratio that puts EVs in

relation to total registrations is that it also accounts for general movements in the car market. It could be the case that, although the total number of registered EVs increases, the increase of ICC registrations exceeds this number, preventing that EVs gain in market share. Thus, only the EV registration ratio would accurately reflect the movement of the EV market share.

As the introduction of EVs to the market is relatively new, there are several countries in the data set that neither exhibit registration values for BEVs nor PHEVs in the first years, leading to zero values for the ratios. While there were no registrations in 17 countries in 2010, only after 2014 each country registered at least one EV. As recommended by different researchers in this field (Kenneddy, 2008; Sprei, 2013; Wooldridge, 2016) the natural logarithm of the ratio is used to ensure normality of the residuals when the dependent variable is a ratio. This in turn means that ratios of 0 become missing observations.

Control Variables: The selection of the control variables is based on the most commonly applied variables as identified in the literature review which can also be considered relevant for an investigation on an international level. These variables also reflect the different categories of determinants of the EV market defined in chapter 3.2.2.1. Most of the selected control variables thereby capture the average value of an indicator for the corresponding country and year. The sources of the control variables, which are discussed in the following, are listed in Table 4.2. In addition, to the sources of the control variables, the table also includes the sources of the main independent variables as well as the dependent variable.

Charging points total per 100km highway: The first control variable that is considered throughout the investigations accounts for the charging infrastructure provided by a country. The charging infrastructure is considered by many scholars (Egbue and Long, 2012; Berkeley et al., 2018; Vergis and Chen, 2015; Wang et al., 2017a; Li et al., 2017) that have performed analyses on individual level, to be an important factor. The results for this determinant on macroeconomic level are however mixed, with several researchers finding an insignificant (Morton et al., 2018; Clinton and Steinberg, 2019) or even a negative (Münzel et al., 2019) influence stemming from this determinant on EV adoption. Nevertheless, most of the research indicates a positive and significant relationship between this determinant and the EV market. Furthermore, as a well developed charging infrastructure contributes to a reduction of range anxiety by EV customers and can be seen as a prerequisite to

operate this vehicle type also on longer distances, data in form of the total number of charging infrastructure points is gathered. Thereby, the number of fast and slow chargers is accumulated and put into relation with the kilometers highways of the respective countries. In this study a ratio variable is preferred, as it can account for the different sizes of the countries. In addition, in this investigation it is argued that putting the number of charging stations in relation to the kilometers highway of a country is more appropriate than building a ratio based on per capita, as it better reflects the charging infrastructure requirement for the size of the traffic system.

Fast chargers per 100km highway: Similar to the first control variable, this variable also accounts for the charging infrastructure of a country. However, in this case only fast chargers and not normal chargers are considered. Incorporating this variable is not as important as accounting for the entire charging infrastructure but could provide information about potential differences in the influence of fast and normal chargers. Keeping in mind that normal chargers require a substantial amount of time to completely load an EV, a greater number of fast chargers could be more attractive to potential EV customers.

Disposable Income: This variable can be important to account for different living conditions between the countries. As EVs are more expensive than comparable ICCs, a positive correlation between disposable income and the registration number of EVs can be assumed.

Fuel Price Ratio: As discussed in the literature review, energy prices were determined to be another significant driver of the EV market. Using a ratio that puts the diesel price in relation to the electricity price controls simultaneously for both fuel prices. It is also more suitable for the investigation, as the ratio represents the fuel related savings a customer receives when switching to an EV. Moreover, a positive side effect is that combining these two variables in one variable saves one degree of freedom in the later analyses. Lastly, following the recommendation of previous literature, the ratio variable is transformed into its natural logarithm. Values for fuel prices were gathered from the EU energy statistical pocketbook (European Commission, 2020, 2018, 2015, 2014, 2013, 2010b) and for electricity prices data was obtained from Eurostat's Energy statistics (Eurostat, 2021c). Thereby, the approach of Münzel et al. (2019) is followed and the average of semi-annual prices for medium-sized households is calculated.

Car Fleet: A country's car fleet can be considered in the investigation to account

for the size of the general car market. As the dependent variable has however the form of a ratio that puts the registration rate of EVs into relation with all registrations, this variable is not of particular importance. This is because using the EV registration ratio already controls for the size of the market. Nevertheless, by considering this variable in the analysis information can be derived whether citizens of countries with a large car market adopt EVs faster.

Available EV Models: The reason for considering a determinant that reflects the number of available EV models in Europe is that it captures the variety of products between which a consumer can choose. This can especially be important in the early years as only a severely limited number of EV models was available.

Trend Variable: The use of a trend variable is recommended in this stream of literature when analysing drivers of the EV market by employing market data. A trend variable is able to account for general time variant developments in the market that take place independent of the considered country. It is for example helpful to account for the continued development of EVs, which is reflected in lower vehicle prices due to decreasing battery prices, improved availability of EV models and other car characteristics. The trend variable is calculated by taking the natural logarithm of the considered years in the investigation.

Dwelling Type House: This variable is another surrogate for the charging capabilities of the citizens within a country. An advantage of EVs is that they can be charged at home if an EV customer purchases a home charging station. A requirement for having the opportunity to charge the vehicle at home is, however, to own a permanent parking spot, preferably in a garage to be able to install such a charging station. As no data for garage ownership is available for the considered countries in this investigation, it is assumed that the percentage of detached and semi-detached houses in a country are the closest proxy that can be used to account for the capability of installing a charging station at home. Detached and semi-detached houses are chosen as they exhibit the highest likelihood that the owners have access to a garage or another permanent parking spot on their property.

Home Ownership Ratio: In the same spirit as the dwelling type house variable, data is collected for the home ownership ratio in the countries. Citizens that own a house are also the most likely to own a garage and therefore have the ability to install a private charging station. Münzel et al. (2019) also argues that people who own a house could have a higher financial security and therefore are better able to afford an EV and a charging station for this vehicle. In addition, researchers have

found that EV ownership correlates with home ownership rates (Tal and Nicholas, 2013; Plötz et al., 2014).

Income Ratio 80 to 20: Similar to disposable income this variable is concerned with the wealth of a population. However, in contrast to disposable income it measures how equally the wealth in a country is distributed. It is hypothesised that countries, where the wealth is more equally distributed, exhibit a higher EV registration rate. The rationale behind this assumption is that more people can afford such a vehicle as the entire wealth is not only focused on a small population percentage in a country. The income ratio 80 to 20, which is also known as the income quintile share ratio, puts the received income of the 20% of the population with the highest income in a country in relation to the income received by the 20% of the population with the lowest income. Hence, the higher the value of this ratio the more unequal the wealth is distributed in a country.

Table 4.2: Data Sources

Variable	Country (if divergent)	Source
EV, BEV, PHEV Registrations		European Commission (2021)
Total New Registrations	Cyprus, Malta	ACEA (2021), European Commission (2021)
EA Twitter		Eurostat (2021f)
EA GT		Samantray and Pin (2019)
		Google (2021)
Innovativeness		Cornell University et al. (2019b,a, 2018, 2017, 2016, 2015)
		Cornell University et al. (2014, 2013); INSEAD (2012, 2011)
		ACEA (2020, 2019, 2018, 2017, 2016)
		ACEA (2015, 2014, 2013, 2012, 2011, 2010)
Subsidies		ÖAMTC (2021); Wikipedia (2021); European Commission (2021)
		Münzel et al. (2019); Government of Malta (2021)
		The Norwegian Tax Administration (2021a,b); Internet Archive (2021)
		Solutii De Mediu (2017); Romania-Insider.com (2016)
Charging Points Total		European Commission (2021)
Fast Chargers		European Commission (2021)
Disposable Income	Malta	Eurostat (2021a)
		CEIC (2021)
		European Commission (2020, 2018, 2015, 2014, 2013, 2010b)
Diesel Price	Switzerland	Bundesamt für Statistik (2021)
	Norway	Statistics Norway (2021)
		Eurostat (2021c)
Electricity Price	Switzerland	Bundesamt für Statistik (2021)
Car Fleet		Eurostat (2021g)
Available EV Models		Tsakalidis and Thiel (2018)
Dwelling Type House		Eurostat (2021b)
Home Ownership Rate		Eurostat (2021d)
Income Ratio 80 to 20		Eurostat (2021e)

Note: When single observations for countries were missing, the Microsoft Excel trend function was applied to achieve a complete data set. This approach is in line with previous literature (Münzel et al., 2019).

4.2.5 Overview of Data Properties and Consideration in the Analyses

Since all research questions in this thesis are concerned with analysing the driving factors of the EV market, the variables considered in the investigations overlap. However, not all variables that have been described in the previous section are included in each of the three studies. Table 4.3 shows, in which study each of these variables has been incorporated into the analysis. The reason for not including a determinant as a control variable in a study differs. One reason is for example that the variable does not correspond with the scope of analysis. Looking at the dependent variable, only the third investigation will distinguish between BEV registration and PHEV registration share in addition to the EV registration share. This is because only in this investigation it is of interest whether the influence of the main independent variable, namely subsidies differs based on the vehicle type. Another reason for the exclusion of a determinant is the restricted availability of data for some variables. As it can be seen in Table 4.3, especially in the investigation of Chapter 8, several control variables cannot be considered in the regression as no data for the year 2020 is available. This however does not necessarily pose a problem, when applying an econometric model that can deal with the omission of variables that embody specific properties. A fixed-effects model for example is able to control for time-invariant and almost time-invariant determinants, which several of the considered control variables can be classified as. On the other hand, the available time frame of the data for the variables also dictates the considered time frame and therefore the sample size of the investigation. For the investigation of the influence of EA on the EV market for example, data for the main independent variable was only available until 2017. Hence, the analysis of this research question is limited to this year, which reduces the sample size. Another example for the influence of data availability on the investigation can be seen in the main independent variable of the second research question. The variable innovativeness is only available in a consistent form, collected from the GII index, for the years 2011 to 2020. This is because a methodological change in the estimation of country innovativeness in the GII framework took place after the year 2010, making the data for the years before 2011 unusable. This leads to the last point that should be considered, when determining which control variables should be included in an analysis. The inclusion of too many variables could result in an over-specification

of the considered model, especially in cases with a small sample size. This is also the reason why the determinants *Dwelling Type House*, *Home Ownership Rate* and *Income Ratio 80 to 20* were for example excluded from the analysis in Chapter 6.

Table 4.3: Considered Variables

Variable	Investigation Considered			Time Availability
	Chapter 6	Chapter 7	Chapter 8	
EV Registration Share	✓	✓	✓	2010-2020
BEV Registration Share			✓	2010-2020
PHEV Registration Share			✓	2010-2020
Twitter EA	✓			2010-2017
GT EA	✓			2010-2017
Innovativeness		✓		2011-2020
Subsidies	✓	✓	✓	2010-2020
Charging Points Total	✓	✓	✓	2010-2020
Fast Chargers	✓	✓	✓	2010-2020
Disposable Income	✓	✓		2010-2019
Electricity to Diesel Price	✓	✓	✓	2010-2020
Car Fleet	✓			2010-2018
Available EV Models	✓			2010-2017
Trend	✓	✓	✓	2010-2020
Dwelling Type House		✓		2010-2019
Home Ownership Rate		✓		2010-2019
Income Ratio 80 to 20		✓		2010-2019

METHODOLOGY

To obtain reliable results in the analysis, appropriate statistical approaches have to be chosen that fit the data-set at hand but also comply with the customs and mathematical rules of the field of research. Consequently, a thorough methodology section should aim to present, discuss and justify all econometric methodologies considered in this investigation. As the scope of the investigation is to determine the causal relationship between the three independent variables of interest and the EV market, the applied approaches are aligned to this goal. In particular, following the conventions in this research stream, different regression techniques are employed to analyse the relationship between the determinants and the considered dependent variable which reflects the development of the EV market. While all statistical analyses are performed with the software Stata, some data visualisations have been created using the software R.

5.1 Classical Linear Regression

As mentioned above, to follow the customs of this research stream different regression models are applied in the main part of the investigation to analyse the causal relationship between the main independent variables and the EV market. Consequently, it makes sense to first provide general information about the methodology behind Ordinary Least Square (OLS) regressions, as most of the later applied statistical approaches are specifications of this method for a panel data structure.

5.1.1 Simple Bivariate Regression Model

A simple bivariate linear regression model describes and evaluates the relationship between a dependent variable and a single independent variable. In an ideal research setting, the changes in the dependent variable can exactly be explained and determined by changes in the independent variable and hence the relationship between these factors can be described with the following model:

$$(5.1) \quad y = \alpha + \beta x$$

where y is the dependent variable, x the independent variable, α the intercept and β the slope of the independent variable. As a model that can determine with absolute certainty the value of the dependent variable is not realistic, a random disturbance term should be added to the equation. Thus, a more realistic econometric model can be described with the following term:

$$(5.2) \quad y_n = \alpha + \beta x_n + \varepsilon_n$$

where ε_n represents the error term and the subscript n denotes the observation number, which can either be cross-sectional or in form of a time series. An important task a researcher encounters is to determine a model that is closest to the straight line relationship as described in Equation 5.1. A model that provides the most accurate estimates should therefore aim to provide a line that fits the data points as closely as possible. One approach to achieve this goal is by minimising the vertical distance between the real data points and the estimates of the model. Hence, the best estimates for α and β can be obtained by minimising the sum of the residuals and in particular the square of the residuals' sum. This approach is known as Ordinary Least Square (OLS) regression. The minimisation problem of the residuals sum of squares (RSS), can mathematically be expressed by the following expression:

$$\min \sum_{n=1}^N \hat{\varepsilon}_n^2$$
$$RSS = (y_n - \hat{y}_n)^2 = \sum_{n=1}^N (y_n - \hat{\alpha} - \hat{\beta}x_n)^2$$

so that the slope $\hat{\beta}$ and the intercept $\hat{\alpha}$ are estimated as:

$$(5.3) \quad \begin{aligned} \hat{\beta} &= \frac{\sum_{n=1}^N (x_n - \bar{x})(y_n - \bar{y})}{\sum_{n=1}^N (x_n - \bar{x})^2} = \frac{Cov[x, y]}{Var[x]} \\ \hat{\alpha} &= \bar{y} - \hat{\beta}\bar{x} \end{aligned}$$

where a hat (^) above a variable denotes the estimated value obtained by the regression model and $\bar{x}$ and $\bar{y}$ indicate the average value of x and y respectively (Brooks, 2019). It should however be noted that the estimates $\hat{\alpha}$ and $\hat{\beta}$ are sample specific, which means that variations in the sample selection within the population would lead to different estimates for these parameters. Consequently, to check for the reliability of the estimates to assess how well they represent the population and to ensure that they do not strongly vary depending on the selected sample, it is important to calculate the standard errors (SEs) of the estimates. This is done by applying the following formula (Brooks, 2019):

$$(5.4) \quad \begin{aligned} SE(\hat{\alpha}) &= s \sqrt{\frac{\sum_{n=1}^N (x_n^2)}{N \sum_{n=1}^N (x_n - \bar{x})^2}} \\ SE(\hat{\beta}) &= s \sqrt{\frac{1}{\sum_{n=1}^N (x_n - \bar{x})^2}} \end{aligned}$$

where the term s represents the standard deviation of the residuals and can be obtained with the formula:

$$(5.5) \quad s = \sqrt{\frac{\sum_{n=1}^N \hat{\epsilon}_n^2}{N - 2}}$$

A smaller value of the SEs can be interpreted in the way that the estimate entails a lower rate of uncertainty and can therefore be considered to be more precise. The calculation of the standard deviation s can further be used as a measure for the SE of the regression.

As it cannot be determined whether the estimate of the slope represents the true population parameter by solely looking at the SE value of a determinant, the concept of hypothesis testing is required as well. In general, a distinction can be made between the null hypothesis H_0 , which states the tested statistical hypothesis, and an alternative hypothesis usually termed H_A , representing the

remaining outcomes of interest. Furthermore, one can differentiate between a two-sided test (e.g. $H_0: \beta = 0$; $H_A: \beta \neq 0$) and a one-sided test (e.g. $H_0: \beta = 0$; $H_A: \beta > 0$ or $\beta < 0$). The latter test can be applied if expectations regarding the effect direction of the determinant exist. Within this framework a proper test-statistic, such as a t-statistic, is calculated, to check whether the null hypothesis can be rejected. This is done by employing the following formula:

$$(5.6) \quad \text{test-statistic} = \frac{\hat{\beta} - \beta^*}{SE(\hat{\beta})}$$

In the context of a regression, the value of β^* reflects the reference value to which the estimated value is compared and is usually 0. The obtained result is then compared with the critical value, which can be derived from a t-distribution with $N-2$ degrees of freedom for a given significance level. Following the test of significance approach, the non-rejection region for the null-hypothesis can be defined as follows (Zhang, 2011):

$$(5.7) \quad -t_{crit} \leq \frac{\hat{\beta} - \beta^*}{SE(\hat{\beta})} \leq +t_{crit}$$

It is not only important to know the significance of the considered variable but also the explanatory power of the entire model, i.e. how well the model fits the data and explains variations in the dependent variable. One of the most widely applied goodness of fit statistics that is consulted for this purpose is the R^2 -value. The R^2 is a ratio that puts the explained sum of squares (ESS), which measures the variation of the estimates of the model around the mean, into relation with the total sum of squares (TSS), which is the sum of the ESS and the RSS. Hence, mathematically the R^2 measure can be defined as:

$$(5.8) \quad R^2 = \frac{\sum_{n=1}^N (\hat{y}_n - \bar{y})^2}{\sum_{n=1}^N (y_n - \bar{y})^2} = \frac{\sum_{n=1}^N (\hat{y}_n - \bar{y})^2}{\sum_{n=1}^N (\hat{y}_n - \bar{y})^2 + \sum_{n=1}^N \hat{\epsilon}_n^2}$$

Due to its ratio properties that put the ESS into relation to the TSS, the goodness of fit measure R^2 is limited to take on values between 0 and 1. Greater values thereby imply a higher explanatory power of the model (Brooks, 2019).

5.1.1.1 Linearity of Regression Function

In order to conduct an OLS regression, it is required that the relationship between the independent and the dependent variable can be expressed by a straight line. Hence, the estimates of the slopes (β) and the intercept (α) must be linear, which does however not necessarily apply to the variables y and x . In contrast to the parameters α and β , variables can often be transformed or manipulated to obtain linear properties. A frequently applied transformation of the variables is the use of the natural logarithm in case exponential growth in the data can be identified or to obtain more normal distributed residuals¹ For example, assuming an exponential regression function of the form:

$$(5.9) \quad Y_n = AX_n^\beta e^{\varepsilon_n}$$

When applying a log transformation to both sides of the equation and considering the laws of logs, equation 5.9 can be rewritten as:

$$(5.10) \quad \ln(Y_n) = \ln(A) + \beta \ln(X_n) + \varepsilon_n$$

When letting $y_n = \ln(Y_n)$ $\alpha = \ln(A)$ and $x_n = \ln(X_n)$, the initial equation 5.2 is obtained. A log transformation of a variable is an important manipulation that is also used throughout the chapters 6, 7 and 8 in this dissertation. It should however be noted that with a transformation of the dependent and independent variables, the estimates also require a different interpretation. To recall, the estimates of a model without any applied transformation are interpreted in such a way that a unit increase in the independent variable leads to an increase reflected by the estimate of β in the dependent variable, if everything else remains the same. In case only the dependent variable is log transformed, an interpretation of the coefficient would be that a unit increase in the independent variable would lead to a percentage increase of y that can be determined with the equation $100*(e^\beta - 1)$. Applying a log transformation to both dependent and independent variable, the results of the regression are interpreted as elasticities. Hence, an interpretation of β would be that the dependent variable increases by the percentage value of the estimate, if the independent variable increases by 1% (Brooks, 2019).

¹Normal distribution of the residuals is an important assumption for OLS regressions which will be discussed in section 5.1.3

5.1.2 Multiple Linear Regression Model

Changes in the dependent variable are often caused by not only one but several factors. Using the example of the EV market, the registration rate of this vehicle type could depend on the price of this vehicle, the charging infrastructure, granted subsidies and more. While it is possible to separately investigate the influence of each variable in an individual regression, a greater validity of the estimates can be achieved when combining all determinants into one regression. In doing so, Equation 5.2 becomes:

$$(5.11) \quad y_n = \alpha + \beta_1 x_{1n} + \beta_2 x_{2n} + \dots + \beta_k x_{kn} + \varepsilon_n$$

where $x_{1n}, x_{2n}, \dots, x_{kn}$ are a set of k explanatory variables of the dependent variable y . The coefficients $\beta_1, \beta_2, \dots, \beta_k$ represent the corresponding estimators of the considered variables that quantify the effect on the dependent variable. In the context of a multiple regression model, the interpretation of the parameter estimates slightly changes. In a multiple regression model, the influence of a variable on the dependent variable is interpreted as a partial effect as the influence of the other explanatory variables is controlled for by eliminating or holding them constant. Equation 5.11 can also be expressed more compact in form of a matrix.

$$(5.12) \quad y = \alpha + X\beta + \varepsilon$$

where y is of dimension $N \times 1$, α is of dimension $N \times 1$, X is of dimension $N \times k$, β is of dimension $k \times 1$ and ε is of dimension $N \times 1$. Consequently, the observations have been stacked up in a vector and all variables are squashed in the X matrix so that each variable is accommodated in one column.

While previously the RSS was minimised in respect to α and β , in a multiple regression the RSS is minimised with respect to the parameters of all variables. The coefficient estimates are obtained from the following expression:

$$(5.13) \quad \hat{\beta} = \begin{pmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \\ \cdot \\ \cdot \\ \hat{\beta}_k \end{pmatrix} = (X'X)^{-1}X'y$$

To obtain the SEs of the variables in a multiple regression, the square root of each of the terms of the leading diagonal of the variance-covariance matrix is used, which can be calculated with the following formula:

$$(5.14) \quad \text{var}(\hat{\beta}) = s^2(X'X)^{-1}$$

where

$$s^2 = \frac{\hat{\varepsilon}'\hat{\varepsilon}}{T-k}$$

and represents the the variance of the errors. The term k in this case determines how many degrees of freedom are lost and is equal to the number of independent variables plus the intercept considered in the regression model.

Building upon the point of losing degrees of freedom when adding more variables to a regression, this concept also becomes important when evaluating the data fit of the model in a multiple regression model. Since the R^2 will always rise when additional variables are added to the regression, the adjusted R^2 is more appropriate for such regressions as it puts into relation the gain in explanatory power and the loss in the degrees of freedom when adding a variable. Another statistic that becomes relevant in the context of multiple regressions is the F-test. By performing this test, it can be checked whether the model is significant when more than one coefficient is used simultaneously (Brooks, 2019).

5.1.2.1 Variable Selection

One approach to determine the most appropriate model specification is not by comparing the explanatory power of different models after they have been established, but rather by implementing a procedure that determines the most suitable variables for a regression. Hence, such an approach directly starts at the beginning of a regression building process with the variable selection. With computational advancements, the endeavours of determining appropriate models with the best data fit became more feasible as with the correct use of statistical softwares numerous different regressions can be executed within a short period of time. One approach that stands out due to its simplicity in its application and its effectiveness, is the General-to-Specific (GTS) approach. The GTS approach is one of the fundamental approaches for econometric model building. It is based on the assumption that the best econometric model for a research is built by first considering every variable

that could influence the dependent variable and including it in a model, which is called the General Unrestricted Model (GUM). Thereafter, several variables are successively dropped from the GUM to obtain a more specific and parsimonious model (Brooks, 2019). The key task of this procedure lies in the decision which variables in particular should be eliminated from the GUM. These decisions are based on t-statistics for the individual variable and F-statistics for the entire model. Moreover, after the deletion of a variable it is tested whether the assumptions of a classical linear regression model are still fulfilled. Continuously going through the model and testing the significance of the variables as well as testing the OLS assumptions after dropping a variable, corresponds to a sequential-testing approach, which can also be considered as a likelihood-based model evaluation. Mathematically, the density function of such a likelihood model y can be defined as:

$$(5.15) \quad L_y(\theta_y) = \begin{cases} f_y(X; \tilde{\theta}_y) & \text{if } \min(\hat{\eta}_y(X; \tilde{\theta}_y) - \eta) \begin{cases} \geq \\ < \end{cases} 0 \\ -\infty & \end{cases}$$

where $f_y(X; \theta_y)$ is the Probability Density Function (PDF) associated with model y at the parameter vector θ_y , for the sample X (Krolzig and Hendry, 2001). The significance levels for the misspecification tests are defined by η , and the corresponding p -values are denoted by $\hat{\eta}$. The vector of p -values, $\hat{\eta}_y(X; \tilde{\theta}_y)$, is evaluated at the maximum likelihood estimate $\tilde{\theta}_y$ under model y and mapped into marginal rejection probabilities. Thus, the PDF of model y is only accepted as the likelihood function in case the sample information complies with the underlying assumptions of the model itself (Krolzig and Hendry, 2001; Vigne, 2017).

In a Monte Carlo setting, the significance levels of the specification tests can be set more dynamically and decided endogenously. For example, in case a misspecification test is failed for the GUM for the desired significance level $\bar{\eta}''$, a reduced significance level $\bar{\eta}' < \bar{\eta}''$ is applied, which is however more binding to pass. Should the GUM also not pass the test with the reduced significance level, the diagnostic test is entirely excluded from the battery of tests (Krolzig and Hendry, 2001). Hence, econometrically for the k^{th} test it can be determined that:

$$\theta_k = \begin{cases} \bar{\eta}'' \\ \bar{\eta}' \\ 0 \end{cases} \quad \text{if } \hat{\eta}_{k,GUM}(X, \tilde{\theta}_{GUM}) \in \begin{cases} [\bar{\eta}'', 1] & \text{desired significance level} \\ [\bar{\eta}', \bar{\eta}'') & \text{reduced significance level} \\ [0, \bar{\eta}') & \text{test excluded} \end{cases}$$

where $0 < \bar{\eta}' < \bar{\eta}'' < 1$.

5.1.3 Assumptions and Properties of the OLS Estimator

In order to make reliable inferences about the coefficients as well as their corresponding SEs, which are obtained from an OLS regression and therefore allow hypothesis testing, the disturbance term of classical linear regression models of the form $y = \alpha + \beta x_n + \varepsilon_n$ must comply with different assumptions.² In total, there are five assumptions that are concerned with the properties of the error term of a linear regression, which are also commonly known as the Gauss-Markov assumptions. In particular these assumptions are (Brooks, 2019):

The first assumption is that the error terms have zero mean, which can be expressed in econometric notation as: $E(u_t) = 0$.

The second assumption maintains that the variance of the errors is constant and finite over all values of x_t . In technical notation this assumption can be defined as follows: $var(u_t) = \sigma^2 < \infty$

Thirdly, it is assumed that the errors are linearly independent of one another; in econometric terms expressed as: $cov(u_i, u_j) = 0$

The fourth assumption states that there is no relationship between the error and corresponding x variate, so that $cov(u_t, x_t) = 0$

Lastly, the fifth assumption requires that the residuals u_t are normally distributed; expressed in mathematical terms as: $u_t \sim N(0, \sigma^2)$.

In case the model meets the first four assumptions for the error terms, it can be concluded that the estimates for $\hat{\alpha}$ and $\hat{\beta}$ derived from an OLS regression incorporate desirable properties. These properties are represented by consistent, unbiased and efficient estimates. In this case the estimates are also commonly referred to as best linear unbiased estimators (BLUE). BLUE is an acronym, where each letter represents a property of the OLS estimator, which are as follows:

Best in this sense means that the estimator $\hat{\beta}$ derived from the OLS exhibits the minimum variance among the class of linear unbiased estimators.

Linear means that the random variable y can be modeled by a linear combination of $\hat{\alpha}$ and $\hat{\beta}$.

The *Unbiased* property of an estimator states that on average, the actual values of $\hat{\alpha}$ and $\hat{\beta}$ will be equal to their true values.

²These also apply to multiple regression models.

Finally, *Estimator* means that $\hat{\alpha}$ and $\hat{\beta}$ are estimators of the true value of α and β .

The previously mentioned fifth assumption of normal distribution of the residuals is not necessarily a requirement to obtain BLUE estimators from an OLS. It rather ensures that valid inferences about the population can be made from the sample estimates of $\hat{\alpha}$ and $\hat{\beta}$ (Brooks, 2019). In the following section, different diagnostic tests are presented which are used throughout this thesis to ensure that the classical linear regression model (CLRM) assumptions are met.

5.1.3.1 Detecting Heteroskedasticity in the Residuals

The assumption of homoskedasticity of the residuals of a regression, which means that the variance of the errors is constant, is one of the major assumptions of the CLRM. A regression model that violates this assumption does not incorporate the minimum variance among the class of unbiased estimators any longer. While no negative influence on the coefficient estimate arises from the issue of heteroskedasticity, the calculation of the corresponding SEs are biased and inefficient. Hence, a reliable determination of the variables' significance is compromised (Brooks, 2019). Before starting to explain how heteroskedasticity can be detected by means of a diagnostic test, it should be noted that heteroskedasticity is also often initially analysed based on a visual analysis. In the visual analysis, the calculated residuals of a regression are plotted against the values of an explanatory variable. One of the most common shapes for heteroskedasticity that can be detected in the idiosyncratic errors is in form of a cone but can however also take on different shapes. By creating such a plot it is possible to make a first assessment of whether the residuals are homoskedastic or not.

To validate the conclusion derived from the visual analysis, formal diagnostic tests can be applied. One of the most commonly applied diagnostic tests in this regard was developed by Breusch and Pagan (1979). For this test, first the residuals of a linear regression model have to be estimated. Assuming a linear regression model of the following form:

$$(5.16) \quad y_t = X_t\beta + u_t \quad (t = 1, \dots, N)$$

A set of residuals u_t is obtained, which are normally and independently distributed and due to the OLS procedure constrained to a zero mean. The variance of

the residuals, denoted as σ_t^2 , can be modeled as follows:

$$(5.17) \quad \sigma_t^2 = h(z_t' \alpha)$$

where the function $h(\cdot)$, which is not indexed by t , possesses first and second order derivatives. α represents a $(p \times 1)$ vector of unrestricted parameters. These parameters are functionally unrelated to the β coefficients of Equation 5.16. As the first element in z_t is unity, it enables to write the null hypothesis of homoskedasticity as follows (Breusch and Pagan, 1979)

$$(5.18) \quad H_0 : \alpha_2 = \dots = \alpha_p = 0$$

and therefore $z_t' \alpha = \alpha_1$ so that $\sigma_t^2 = h(\alpha_1) = \sigma^2$ is constant.

To test the null hypothesis of homoskedasticity in the residuals, a Lagrange Multiplier (LM) statistic is applied. Represented by the parametric constraints $\phi(\theta) = 0$ the LM statistic is given by (Breusch and Pagan, 1979):

$$(5.19) \quad LM = \hat{d}' \hat{\Psi}^{-1} \hat{d}$$

The hats above the parameters indicate that the quantities are evaluated with $\hat{\theta}$, the restricted maximum likelihood estimate satisfying $\phi(\hat{\theta}) = 0$ (Breusch and Pagan, 1979). Furthermore, $\Psi = -E(\frac{\partial^2 l}{\partial \theta \partial \theta'})$ represents the information matrix $\Psi = -E(\frac{\partial^2 l}{\partial \theta \partial \theta'})$ and d ($d = \frac{\partial l}{\partial \theta}$) is the first derivative vector in regard to the parameters θ .

In case heteroskedasticity is detected in the residuals, a potential solution to counteract the biases arising from this issue is to employ heteroskedasticity-consistent standard errors.

5.1.3.2 Detecting Serial Correlation in the Residuals

The presence of serial or autocorrelation in the idiosyncratic errors is an explicit violation of the third assumption for OLS regressions, that error terms are independent from each other. The consequences of serial correlation in the error terms is inefficiency in the coefficient estimates which is expressed in biased SEs. Hence, in case a model is affected by serial correlation and remains untreated, wrong inferences about the significance of the variables could be made (Brooks, 2019). Serial

correlation also poses a problem to panel-data models. To detect whether serial correlation is present in the idiosyncratic errors of a panel data model, indifferent to whether it is a FE or RE model, Wooldridge (2002) developed a diagnostic test which is applicable under general conditions and functions as follows: Assume a linear one-way model:

$$(5.20) \quad y_{it} = \alpha + \mathbf{X}_{it}\beta_1 + \mathbf{Z}_i\beta_2 + \mu_i + \epsilon_{it} \quad i \in \{1, 2, \dots, N\} \quad t \in \{1, 2, \dots, T_i\}$$

where y_{it} is the dependent variable; $\mathbf{X}_{it}$ is a $(1 * K_1)$ vector of time-varying covariates and $\mathbf{Z}_i$ is a $(1 * K_2)$ vector of time-invariant covariates; α , β_1 , and β_2 are $1 + K_1 + K_2$ parameters; μ_i is the individual level effect and ϵ_{it} is the idiosyncratic error (Drukker, 2003). Depending on whether the error term ϵ_{it} is correlated with the variables of the $\mathbf{X}_{it}$ and the $\mathbf{Z}_i$ vector, the covariates of the vectors can either be estimated with a regression with within-transformed data (FE) or a feasible generalized least squares approach, also known as random-effects regression. In case the error term is correlated with the covariates of the two vectors, only the covariates of the time-varying covariates $\mathbf{X}_{it}$ can be consistently estimated with a regression with within-transformed data or first differenced data. However, if there is no correlation between the error terms and the covariates of $\mathbf{X}_{it}$ and $\mathbf{Z}_i$, the covariates of both vectors can be efficiently estimated with an RE method. A more detailed discussion on the differences between FE and RE approaches takes place in Chapter 5.2 but can also be found in Baltagi (2001) or Wooldridge (2002).

To detect whether the assumption of no serial correlation in the residuals holds, or expressed in econometric terms $E[\epsilon_{it}\epsilon_{is}] = 0$ for all $s \neq t$, the approach of Wooldridge (2002) relies on the residuals obtained from a first-differences approach with the following form:

$$(5.21) \quad \begin{aligned} y_{it} - y_{it-1} &= (\mathbf{X}_{it} - \mathbf{X}_{it-1})\beta_1 + \epsilon_{it} - \epsilon_{it-1} \\ \Delta y_{it} &= \Delta \mathbf{X}_{it}\beta_1 + \Delta \epsilon_{it} \end{aligned}$$

where Δ is the first-difference operator (Drukker, 2003). In the procedure outlined by Wooldridge (2002), the initial objective is to obtain the estimates of the residuals $\hat{\epsilon}_{it}$. This is achieved by estimating the parameters of β_1 by regressing Δy_{it} on $\Delta \mathbf{X}_{it}$. One of the key aspects of the procedure is to verify whether $\text{Corr}(\Delta \epsilon_{it}, \Delta \epsilon_{it-1}) = -0.5$. This is based on the finding by Wooldridge (2002) who

discovered that when this condition is fulfilled, the error terms ϵ_{it} do not exhibit serial correlation. Based on this prerequisite, the residuals $\hat{e}_{it}$ obtained from the first difference regression are regressed on their own lags. Furthermore, the errors in this regression are clustered at panel level, to account for within-panel correlation of $\hat{e}_{it}$ on $\hat{e}_{it-1}$. In the consecutive step it is checked whether the coefficients of the lagged residuals are equal to -5 (Drukker, 2003).

5.1.3.3 Estimator Consistency

As already mentioned, one important property of an estimator is its consistency, which requires the estimates of a regression to not be correlated with the error term (Brooks, 2019). In some cases, an estimator is known that is consistent but inefficient and a second estimator is available which is more efficient but it is unknown whether the estimates are consistent. To determine whether the estimates of the more efficient estimator is also consistent, Hausman (1978) developed a specification test that compares the consistent but inefficient estimator $\hat{\theta}_1$ to the efficient estimator $\hat{\theta}_2$, for which the consistency is unknown. The underlying assumption of the test procedure is that no systematic difference in the estimates obtained from the two estimators should exist, if the efficient estimator is consistent as well (Stata Corporation, 2017).

In a standard regression framework of the form $y = X\theta + \epsilon$, consistency and efficiency are reflected by the two stochastic specifications that the conditional expectation of ϵ given x is zero and that ϵ have a spherical covariance matrix. In econometric terms these specifications can be defined as follows:

$$(5.22) \quad E(\epsilon|x) = 0$$

and

$$(5.23) \quad V(\epsilon|x) = \sigma^2 I$$

While failure of the first assumption is according to Hausman (1978) more worrisome as it would lead to biased estimates, he criticises that most test statistics in the field of econometrics are rather concerned with the second assumption. Based on this criticism Hausman (1978) proposed an approach that rather focuses on testing the assumption described in Equation 5.22 and hence the consistency of the more efficient estimator. In the test procedure, the null hypothesis is reflected

by the assumption that $\hat{\theta}_2$ is an efficient as well as consistent estimator of the true parameters (Vigne, 2017). To test whether a significant difference between the estimates of estimator $\hat{\theta}_2$ and the consistent estimator $\hat{\theta}_1$ by simultaneously noting that their difference is uncorrelated with the efficient estimator when the null hypothesis is true, an expanded regression framework can be applied and tests be devised from the regression (Hausman, 1978):

$$(5.24) \quad y = X\theta + \tilde{X}\alpha + v$$

where $\tilde{x}$ is a suitably transformed version of x and the tests are performed under the null hypothesis that $\alpha = 0$ (Hausman, 1978). The final Hausman statistic is computed as follows (Stata Corporation, 2017):

$$(5.25) \quad H = (\beta_c - \beta_e)'(V_c - V_e)^{-1}(\beta_c - \beta_e)$$

where β_c and V_c are the coefficient vector and covariance matrix of the consistent estimator $\hat{\theta}_1$, respectively and β_e and V_e are the respective counterparts for the efficient estimator $\hat{\theta}_2$. Moreover, the Hausman statistic is distributed as χ^2 with the degrees of freedom equal to the rank of the difference in the variance matrices.

5.1.3.4 Detecting Multicollinearity between the Explanatory Variables

The absence of multicollinearity is an implicit assumption of the OLS procedure. Estimating coefficients with an OLS approach in the presence of multicollinear variables does not strictly violate the BLUE properties of the OLS estimators but could distort the SEs of the variables by inflating them. This is a consequence of the difficulty the OLS procedure has in clearly assigning the effect of a determinant on the dependent variable when explanatory variables are strongly correlated with each other (Brooks, 2019).

A widely applied test statistic to formally detect multicollinearity between the explanatory variables is the *variance inflation factor* (VIF) test. With the VIF test, a factor for each variable can be estimated that determines the effect of how much the parameter estimate is inflated due to collinearity with other explanatory variables in a multiple regression model. The precise final interpretation of the score would be that the variance of the parameter in the case that the variable is linearly independent from the other explanatory variables, can be determined by

dividing the variance by the obtained VIF score (Brooks, 2019). The VIF score of each explanatory variable can be calculated as follows:

$$(5.26) \quad VIF_j = \frac{1}{(1 - R_j^2)}$$

Hence, the VIF score for the j^{th} explanatory variable is calculated by using the R_j^2 value of this variable. This is obtained by regressing this variable on the remaining predictors. The formula is derived from the part that determines the correlation between the variable x_j and other predictors in a multiple regression of the formula to calculate the sampling variance of a parameter, which is given by (Wooldridge, 2016):

$$(5.27) \quad Var(\hat{\beta}_j) = \frac{s^2}{(1 - R_j^2) \sum_{i=1}^n (x_{ij} - \bar{x}_j)^2} = \frac{s^2}{\sum_{i=1}^n (x_{ij} - \bar{x}_j)^2} * VIF_j$$

where s^2 is the variance of the error terms, and R_j^2 as explained above the R^2 value obtained from regressing x_j on all other explanatory variables (Wooldridge, 2016).

To assess when multicollinearity becomes an issue for a regression model based on the evaluation of the VIF score is subject to a researcher's individual discretion, as no particular threshold value exists that explicitly indicates the presence of severe multicollinearity between the variables. However, as a rule of thumb VIF scores of 10, or alternatively, more conservative, 5 are applied by many researchers as a cutoff point when multicollinearity could have significant influence on the inferences that can be made from the estimates of a regression model. Different remedies to encounter multicollinearity such as ignoring it, dropping one of the multicollinear variables or transforming the highly correlated variables into a ratio are proposed. Another possible means of reducing multicollinearity which is however not always feasible is to increase the sample size. Multicollinearity in the presence of a panel data set does however not pose such a significant problem as the additional variation that is introduced to the model by looking at the behavior of different entities over time minimises this issue (Brooks, 2019).

5.1.3.5 Detecting Misspecification of the Regression Model

One of the implicit assumptions of the CLRM is that the model is correctly specified. In particular, this means that the relationship between the dependent and

independent variables can be described by a straight line. This means that the parameters of the explanatory variables in a regression model are linear (Brooks, 2019). To test whether a regression model has the correct functional form, different diagnostic tests can be applied. Amongst others, the Ramsey RESET test is due to its simplicity one of the most commonly employed test statistics to detect potential misspecification of the regression model (Ramsey, 1969). The idea behind the Ramsey RESET test is simple, as it assumes that adding higher order terms of the fitted values, for example in the form of squares or cubes, to the original regression model, and subsequently performing a joint significance test of the additional regressors, allows the identification of whether the functional form of the model is misspecified (Wooldridge, 2016). In econometric terms, a standard regression model as for example shown in Equation 5.11, where fitted values of the dependent variables are added to obtain such an auxiliary regression, can be defined as follows:

$$(5.28) \quad y_t = \alpha_1 + \alpha_2 \hat{y}_t^2 + \alpha_3 \hat{y}_t^3 + \dots + \alpha_p \hat{y}_t^p + \sum \beta_i X_{it} + \epsilon_t$$

The fitted values of y with its powers of higher order ($\hat{y}_t^2$, $\hat{y}_t^3$, etc.) are capable of capturing nonlinear relationships not identified by the original model, if present. This is due to the fact that they incorporate higher order powers of the original explanatory variables (Brooks, 2019). Consequently, in case one of these higher power fitted values is significant, evidence for a misspecification of the linear model exists. Testing the significance of the variables can be done with a joint significance test such as an F-test, with the hypothesis that the parameters α_2 , α_3 , ... and α_p of Equation 5.28 are zero.

5.2 Linear Panel Data Models

The longitudinal structure of the collected data described in the previous chapter, helps overcome the lack of observations cross sectionally and over time by incorporating and merging information of both dimensions. Hence, econometrically the simple bivariate regression model 5.2³ can be modified as follows:

³In this chapter, for simplicity, panel data regressions are only explained in the bivariate case, where applicable.

$$(5.29) \quad y_{it} = \alpha + \beta x_{it} + \varepsilon_{it} \quad i = \{1, 2, \dots, N\} \quad t = \{1, 2, \dots, T\}$$

where the subscripts i denote the observations of the entities and t the time period. An easy way to process the data would be the application of a pooled OLS, which does not consider the space and time dimension of the data set. Hence, in this regression approach all data points would be stacked up in a single column vector for the dependent y and similarly the independent x variable. Although this approach is relatively easy to perform, it requires that specific assumptions about the relationship of the independent variables and the dependent variables are fulfilled. For example, it requires that the average value of the variables are constant and the relationship between them and the considered cross sectional units does not change over time (Brooks, 2019).

There are however, also other approaches available that can handle the panel data structure, from which a few are discussed in the following sub-chapters. The correct application of these models provides specific advantages, which are not available with a simple cross sectional or time series OLS regression, as they allow the researcher to fully benefit from the abundant structure of panel data which itself exhibits several advantages. One of them is the ability to more easily gather larger data sets, as the cross sectionality of the data reduces the need for excessively long time periods to obtain a similar size. This in turn leads to more degrees of freedom and hence a higher validity of the estimates. Moreover, the combination of time series and cross sectional data improves the variation in the data set, reducing the possibility of multicollinearity. A last advantage that should be stated is that with a specific structuring of the panel data model, drawbacks arising from omitted variables can be eliminated. Thus, it is not surprising that panel data techniques are predominantly applied throughout the thesis to analyse the research questions developed in the literature review.

5.2.1 Fixed Effects Model

One widely applied panel data regression approach in the field of finance is fixed effects (FE) models. The simplest FE model can be obtained by decomposing the error term of a simple regression model such as presented in Equation 5.29 into its individual unit effects v_i and the remainder disturbance ε_{it} . Thus, Equation 5.29 can be rewritten as (Brooks, 2019):

$$(5.30) \quad y_{it} = \alpha + \beta x_{it} + v_i + \varepsilon_{it}$$

Hence, the specific unit effect is capable of accounting for cross entity differences that do not change over time. Practically, the unit effects in the model can be represented by including dummy variables for each entity, wherefore it is termed least squares dummy variable (LSDV) approach. Econometrically, Equation 5.30 can be modified to

$$(5.31) \quad y_{it} = v_1 D1_i + v_2 D2_i + \dots + v_N D N_i + \beta x_{it} + \varepsilon_{it}$$

where $D1_i$ is the dummy variable that takes on the value 1 for all observations of the first cross sectional unit and zero otherwise, $D2_i$ is the dummy variable that takes on the value 1 for all observations of the second cross sectional unit and zero otherwise, and so on. The downside of the LSDV approach is however, that due to adding dummy variables to the regression model, it includes $N + k$ parameters, wherefore the regression becomes more cumbersome to be estimated. This can especially be a problem if the N dimension is large (Brooks, 2019). Hence, to avoid the inclusion of dummy variables and simplify the estimation of the model another FE approach, which is also known as the *within-estimator* was developed. Following the approach of the *within-estimator*, a within transformation can be applied to the dependent and all explanatory variables. This means that the time mean of each variable of each entity of the panel is deducted from all observations of each variable of each entity of the panel. As a consequence time-invariant effects of the entities i are eliminated as they are subtracted from the model. Thus in econometric terms, the following regression model is obtained:

$$(5.32) \quad (y_{it} - \bar{y}_i) = (x_{it} - \bar{x}_i)\beta + (\varepsilon_{it} - \bar{\varepsilon}_i)$$

where $\bar{y}$ represents the time average of the dependent variable for each variable and can be defined as $\bar{y}_i = \frac{1}{T} \sum_{t=1}^T y_{it}$; similarly the time averages for the explanatory variables are calculated. Moreover, no intercept is required as the dependent variable has zero mean by construction (Brooks, 2019). Both the within-estimator and the LSDV approach will yield the same results. The advantage of a within-estimator is that it does not require the estimation of the dummy variables. Applying an

FE approach, the β parameters are then basically estimated by using OLS (Stata Corporation, 2017).

In terms of consistency, the FE estimator is a good approach as it automatically controls for differences between the panels. However, the gain in consistency of the estimates by including dummy variables in the LSDV approach or demeaning the observations in a panel when considering the within-estimator, comes at the cost of efficiency due to significant losses in the degrees of freedom. Another downside of this approach is that time-invariant variables cannot be estimated as they are either captured by the panel-specific dummy variables or eliminated due to the demeaning procedure of the variables. Hence the FE approach can only consider within unit variation and neglects between unit variations (Brooks, 2019).

5.2.2 Random Effects Model

A panel data model that considers both within and between variation of the panels in the regression is the random effects (RE) model. As a consequence, this model does not employ an OLS approach but relies on a matrix weighted average of the estimates, also known as Generalized Least Square (GLS) approach, which are produced by the between and within estimators (Stata Corporation, 2017). In econometric terms, the RE estimator can be expressed as follows:

$$(5.33) \quad (y_{it} - \theta \bar{y}_i) = (1 - \theta)\alpha + (x_{it} - \theta \bar{x}_i)\beta + \{(1 - \theta)v_i + (\varepsilon_{it} - \theta \bar{\varepsilon}_i)\}$$

where θ is a function of the variance of the observation error term σ_ε^2 and of the variance of the entity-specific error term σ_v^2 (Brooks, 2019). At this stage it should be noted that in contrast to the FE approach the entity-specific error term measures the random deviation of each entity's intercept term from the global intercept α rather than representing an intercept for each entity (Brooks, 2019). The aforementioned function of θ is $\hat{\theta} = 1 - \sqrt{\frac{\hat{\sigma}_\varepsilon^2}{T_i \hat{\sigma}_u^2 + \hat{\sigma}_\varepsilon^2}}$. Hence, for the dependent variable, explanatory variables and error term, a partial mean instead of the entire mean will be deducted from the observations. Employing this transformation it should be ensured that no cross correlations in the error terms exist (Brooks, 2019).

Since no panel dummy variables are included and no within transformation of the dependent and independent variables takes place in the RE approach, this procedure does not exhibit as many losses in degrees of freedom as the FE approach does. Hence, the estimates of the RE approach can be considered more efficient

compared to those of the FE approach. Another advantage of this approach is that since it only includes a global intercept and not one for each entity in the panel, RE models are also able to consider the variation between the entities. Consequently, time-invariant variables can also be estimated with this approach. On the contrary, an RE model is only applicable if the error term (ε_{it} and v_i) is uncorrelated with all explanatory variables. Hence, the requirement is stricter than those for the FE approach, which can account for different omitted variables due to the considered panel specific dummy variables or within-transformation of the variables. The assumption of no correlation between the error terms and the explanatory variables is often violated, as it is difficult to capture all entity specific differences in the model. In case this assumption is violated, the RE estimator will provide biased and inconsistent results (Brooks, 2019).

5.2.3 Between Effects Model

As already touched upon in the previous panel model description, another panel data model that is not as frequently used as the RE or FE approach is the between estimator. The between estimator is simply a cross sectional regression, in which the time averaged values of the observations of the panels are used. Econometrically the between estimator can be defined as follows (Stata Corporation, 2017):

$$(5.34) \quad \bar{y}_i = \alpha + \bar{x}_i\beta + v_i + \bar{\varepsilon}_i$$

The regression model is therefore equal to the part that is used to demean Equation 5.30 that is applied to obtain the within estimator expressed in Equation 5.32 and partly demean Equation 5.30 to derive to the RE estimator (Stata Corporation, 2017). In comparison to the within estimator, the between estimator as a regression model on its own incorporates the advantage that by averaging the observations within a unit, the influence of measurement errors are likely to be reduced. A downside of this method is however that it often yields insignificant results for the considered variables, since averaging the observations within the units leads to reduced numbers of observations (Blaydes, 2006).

5.2.4 Mixed Effects Models

Applying either an FE or RE approach almost always entails a trade-off between efficiency and consistency of the estimates. While the estimates of the RE approach can be considered more efficient since less degrees of freedom are required for the regression process, an FE approach is regarded in many cases to be more consistent. This is due to the inclusion of entity specific dummy variables which account for time-invariant differences between the panels and therefore minimise the possibility of omitted variable bias. Another issue that arises from the inclusion of entity dummy variables is that time-invariant variables, also known as *level 2* variables, cannot be estimated with the FE approach. Moreover, slowly changing variables, also known as *sluggish variables*, strongly correlate with the entity specific dummies and are due to the lack of within variation often insignificant (Bartels, 2008; Williams, 2018). This does not pose a problem, if the variable of interest exhibits a high within unit variation but is definitely an issue when trying to determine the significance of a slowly changing variable. To encounter the issue that an FE approach is not able to provide estimates for a level 2 variable and an RE model might provide biased estimates, *mixed effects* models were developed. These models propose to estimate within effects in RE models (Allison, 2009; Wooldridge, 2010; Schunck, 2013). In the following the methodology behind two mixed effects models, namely the *hybrid model* and the *correlated random effects model*, are presented. The methods that are introduced are of particular interest for the analysis in Chapter 7.

5.2.4.1 Hybrid Model

The idea behind the *hybrid model* is to decompose the within and between effects of the panel units and estimate the respective effects in a single regression model. As mentioned above, the basis of this approach is an RE model that can be described with the following equation (Schunck, 2013):

$$(5.35) \quad y_{it} = \alpha + \beta_1 x_{it} + \beta_2 c_i + v_i + \varepsilon_{it}$$

where the variable c_i represents a determinant that is time-invariant and only differs between units, also known as level 2 variable; the variable x_{it} represents a level 1 variable as in the previous regression models; v_i the error term of the level 1 variable and ε_{it} the error term of the level 2 variable. To obtain a within estimate

in this RE setting, the level 1 variables should be demeaned based on their clusters like in the FE approach ($x_{it} - \bar{x}_i$), which consequently provides the same estimates for the variable as the FE model. Moreover, the level 1 variable can further be decomposed into a between component ($\bar{x}_i = n_i^{-1} \sum_{t=1}^{n_i} x_{it}$). Although, the inclusion of this component is not required, controlling for the cluster mean of level 1 variables should ensure that between cluster differences of the time variant variable x_{it} do not impact the level 2 variables. Econometrically, the following formula is obtained (Schunck, 2013):

$$(5.36) \quad y_{it} = \alpha + \beta_1(x_{it} - \bar{x}_i) + \beta_2 c_i + \beta_3 \bar{x}_i + v_i + \varepsilon_{it}$$

It should be kept in mind that the estimate obtained for β_1 is, although modeled in an RE model, not more efficient compared to when applying an FE approach as the estimate solely relies on the within variation of this variable. Additionally, it has to be considered that $E(v_i | x_{it}, c_i) = 0$ and $v_i | x_{it}, c_i \sim N(0, \sigma^2)$ still have to hold to derive an unbiased estimate of the parameter β_2 . An advantage of this approach is that it allows to test for the equivalence of the within and between component of each variable individually and therefore provides the opportunity to analyse whether an RE specification might already suffice. The approach to test for the equivalence of the components is known as an augmented regression and considered to be a more flexible diagnostic test than the Hausman test (Jones et al., 2007; Andreß et al., 2013; Schunck, 2013). Employing Equation 5.36 as an example, it can be tested whether the estimate $\beta_1 = \beta_3$. If this is the case, it can be concluded that the estimates are not significantly different and Equation 5.36 collapses to Equation 5.35, the RE model (Jones et al., 2007; Schunck, 2013).

5.2.4.2 Correlated Random Effects Model

Another mixed effects model that is closely related to the hybrid model is the correlated random effects (CRE) model developed by Mundlak (1978). In the CRE model the unit mean of each panel of a variable is used to relax the assumption of a zero correlation between the level 2 error and the level 1 variables. Hence the level 2 error can be defined as $v_i = \pi \bar{x}_i + \mu_i$ and Equation 5.35 becomes (Schunck, 2013):

$$(5.37) \quad y_{it} = \alpha + \beta_1 x_{it} + \beta_2 c_i + \pi \bar{x}_i + \mu_i + \varepsilon_{it}$$

Thus, including the cluster mean of a level 1 variable is a viable alternative to demeaning such a variable, as it accounts for the correlation between the level 2 error and the time-variant variable. In the CRE model, the parameter of the cluster mean variable does however not represent the estimate for the between effect but expresses the difference of the within and between effects. Hence, in this model the parameter π can be interpreted as the difference between the within estimator and the between estimator from the hybrid model, so that $\pi = \beta_3 - \beta_1$ (Mundlak, 1978; Schunck, 2013). The parameter β_1 yields the same estimates as the FE and hybrid model (Wooldridge, 2010; Schunck, 2013). Moreover, it is also possible to carry out an augmented regression with the CRE model. However, since π already represents the difference between the within and between effects, for the CRE model it is tested whether π is significantly different to 0. If π is not significantly different to 0 this confirms that an RE approach can be applied.

5.3 Dynamic Panel Data Models

In a linear dynamic panel data model p lags of the dependent variable are included as covariates in the regression model, implying that the dependent variable depends on its own previous values (Roodman, 2009; Stata Corporation, 2017). The idea behind including lags of the dependent variable as explanatory variables is to account for unobserved fixed or random panel-level effects (Stata Corporation, 2017; Vigne, 2017). The issue that arises from the inclusion of a lagged dependent variable on the right hand side of the equation is that by construction these additional variables correlate with the unobserved panel-level effects. This means that assumption 4 of the CLRM is violated, leading to inconsistent standard estimators when applying a traditional FE or RE model as discussed in the previous sections (Stata Corporation, 2017). Consequently, this section of the methodology is dedicated to presenting econometric approaches that can tackle this problem. Thereby, the following classical linear dynamic panel data model shall be considered (Stata Corporation, 2017):

$$(5.38) \quad y_{it} = \sum_{j=1}^p \alpha_j y_{i,t-j} + x_{it} \beta_1 + w_{it} \beta_2 + v_i + \epsilon_{it} \quad i = 1, \dots, N \quad t = 1, \dots, T_i$$

where the subscript i denotes the number of entities and the subscript t the number of observations for each panel; α_j represents the p parameters that are

estimated for the number of lagged dependent variables $y_{i,t-j}$ considered in the regression; x_{it} in this regression model reflects a $1 \times k_1$ vector of strictly exogenous covariates and w_{it} is a $1 \times k_2$ vector of predetermined and endogenous covariates. β_1 and β_2 are the respective $k_1 \times 1$ and $k_2 \times 1$ vectors of the parameters of x_{it} and w_{it} . Lastly, v_i are the potentially correlated panel-level effects and ϵ_{it} are the i.i.d. error terms over the whole sample with variance σ_ϵ^2 . The panel-level effects and error terms are assumed to be independent for each i over all t .

5.3.1 First Difference GMM

The first method that is introduced is known as the difference generalized method of moments (GMM) approach developed by Arellano and Bond (1991). The approach is called first difference GMM as estimator consistency is obtained by using the first-difference to remove panel-level effects and by using instruments as well as the first differenced errors from Equation 5.38 to form moment conditions (Stata Corporation, 2017). The first difference GMM approach builds on the work of Anderson and Hsiao (1981, 1982) on dynamic panel data models and Holtz-Eakin et al. (1988) on vector autoregression coefficients which Arellano and Bond (1991) combine with the GMM framework developed by Hansen (1982), to develop an approach that establishes a large instrument matrix. This GMM approach requires a data set in form of many panels and few time periods (large n and small t). Moreover, a second requirement for the approach to be applicable is that the idiosyncratic errors are not autocorrelated (Stata Corporation, 2017). The GMM estimator $\hat{\alpha}$ is based on the sample moments $N^{-1} \sum_{i=1}^N Z_i' \bar{v}_t = N^{-1} Z' \bar{v}$ and given by the following equation:

$$(5.39) \quad \hat{\alpha} = \underset{\alpha}{\operatorname{argmin}} (\bar{v}' Z) A_N (Z' \bar{v}) = \frac{\bar{y}'_{-1} Z A_N Z' \bar{y}}{\bar{y}'_{-1} Z A_N Z' \bar{y}_{-1}}$$

where $\bar{v} = \bar{y} - \alpha \bar{y}_{-1} = (\bar{v}'_1, \dots, \bar{v}'_N)'$ is a $N(T-2)1$ vector and $Z = (Z'_1, \dots, Z'_N)'$ is a $N(T-2) \times m$ matrix (Arellano and Bond, 1991; Vigne, 2017). To obtain the one-step estimator $\hat{\alpha}_1$, A_N is set to be $A_N = (N^{-1} \sum_i Z_i' H Z_i)^{-1}$ where H is a $(T-2)$ square matrix with twos in the main diagonal, minus one in the first sub-diagonals and zero otherwise (Arellano and Bond, 1991). On the contrary the two-step estimator $\hat{\alpha}_2$ is obtained by setting $A_N = \hat{V}_N^{-1}$ (Hansen, 1982).

The parameters $\hat{\beta}$ of the exogenous variables can be obtained as follows (Arellano and Bond, 1991; Vigne, 2017):

$$(5.40) \quad \hat{\beta} = (\bar{X}' Z A_N Z' \bar{X})^{-1} \bar{X}' Z A_N Z' \bar{y}$$

where $\bar{X}$ is a stacked $(T-2)N \times k$ matrix of observations on $\bar{x}_{it}$. Like above, alternative choices of A_N will produce one-step and two-step estimators.

5.3.2 System GMM

The system GMM was developed by Blundell and Bond (1998) and is an extension of the difference GMM described in the previous section and builds on the work of Arellano and Bover (1995). This method addresses the issues that the lagged-level instruments in the difference GMM model becomes weak in case when either the autoregressive process becomes too persistent or the ratio of the variance of the panel-level effects v_i to the variance of the idiosyncratic error ε_{it} becomes too large (Stata Corporation, 2017). In particular, to encounter this issue, the researchers propose a model that employs lagged differences as instruments for the level equation in addition to the instruments in levels that are used for the first differenced equation (Bruno, 2005b; Stata Corporation, 2017). It should however be noted that the additional moment conditions are only valid in case $E[v_i \Delta y_{i2}] = 0$ holds for all i (Stata Corporation, 2017).

In econometric terms, following the system GMM of Blundell and Bond (1998), $\hat{\alpha}$ can be obtained from the following formula (Blundell and Bond, 1998):

$$(5.41) \quad \hat{\alpha} = \hat{\alpha}_{dif} = (\bar{y}'_{-1} Z A_N Z' \bar{y}_{-1})^{-1} \bar{y}'_{-1} Z A_N Z' \bar{y}$$

where $\bar{y}'_i$ is the $(T-2)$ vector $(\Delta y_{i3}, \Delta y_{i4}, \dots, \Delta y_{iT})$ and $\bar{y}'_{i,-1}$ is the $(T-2)$ vector $(\Delta y_{i2}, \Delta y_{i3}, \dots, \Delta y_{i,T-1})$ (Blundell and Bond, 1998; Vigne, 2017). Furthermore, as in the difference GMM case the matrix A_N needs to be defined. According to Blundell and Bond (1998) the optimal weights of A_N are given as follows:

$$(5.42) \quad A_N = (N^{-1} \sum_{i=1}^N Z'_i \hat{u}_i \hat{u}'_i Z_i)^{-1}$$

where $\hat{u}_i$ are the residuals of an initial consistent estimator, also known as a two-step GMM estimator (Blundell and Bond, 1998).

5.3.3 A Linear Dynamic Panel Data Model Allowing for Autocorrelation in the Idiosyncratic Errors

As pointed out in the two previous sections the difference and system GMM are commonly applied approaches that can deal with the correlation issue between the lagged dependent variables and the unobserved panel level effects in a regression model. A limitation of both models is however, that they are not applicable when the idiosyncratic errors are autocorrelated. The Arellano and Bond (1991) and Blundell and Bond (1998) model can however be respecified in such a way that the idiosyncratic errors follow a low-order moving average (MA) process, which enables the models to deal with autocorrelation. Econometrically, a linear dynamic panel data model with autocorrelation in the errors is derived as follows. First, assume a classic dynamic panel data model as presented in Equation 5.38, where x and w contain lagged independent variables and time dummies. Furthermore, define X_{it}^L as a $1 \times K$ vector of covariates for i at time t with the form $\mathbf{X}_{it}^L = (y_{i,t-1}, y_{i,t-2}, \dots, y_{i,t-p}, x_{it}, w_{it})$, where the superscript L denotes the variables to be levels. K in this case is $K = p + k_1 + k_2$ with p representing the number of included lags; k_1 as the number of strictly exogenous variables in x_{it} , and k_2 as the number of predetermined variables in w_{it} (Stata Corporation, 2017). With these assumptions Equation 5.38 can be rewritten as a set of T_i equations for each individual (Stata Corporation, 2017):

$$(5.43) \quad y_i^L = \mathbf{X}_i^L \delta + v_i t_i + \epsilon_i$$

T_i stands for the number of observations available for individual i . While y_i , t_i and ϵ_i are $T_i \times 1$, $\mathbf{X}_i$ is $T_i \times K$.

In equation 5.43 both untransformed and transformed variables are used by the estimators. The transformation of the variables can for example take on the form of first differencing or creating forward-orthogonal deviations. To identify the transformed variables, they are marked with an $*$ in the following. Hence, stacking the transformed and untransformed matrices of the covariates for a given i yields:

$$(5.44) \quad \mathbf{X}_i = \begin{pmatrix} \mathbf{X}_i^* \\ \mathbf{X}_i^L \end{pmatrix}$$

In addition an instruments matrix Z_i needs to be defined, which exhibits the following form (Stata Corporation, 2017):

$$(5.45) \quad \mathbf{Z}_i = \begin{pmatrix} \mathbf{Z}_{di} & 0 & \mathbf{D}_i & 0 & \mathbf{I}_i^d \\ 0 & \mathbf{Z}_{Li} & 0 & \mathbf{L}_i & \mathbf{I}_i^L \end{pmatrix}$$

where $\mathbf{Z}_{di}$ represents the GMM-type instruments obtained from the first difference equation, $\mathbf{Z}_{Li}$ is the GMM-type instrument's counterpart derived from the level equation; the standard instrument matrices for the difference and level equation are represented by $\mathbf{D}_i$ and $\mathbf{L}_i$, respectively; Lastly, $\mathbf{I}_i^d$ and $\mathbf{I}_i^L$ denote the matrices of the standard instruments for the differenced errors and level errors, respectively (Vigne, 2017; Stata Corporation, 2017).

Based on all the above, the one step estimates of the parameter β are given by

$$(5.46) \quad \hat{\beta}_1 = \mathbf{W}_1^{-1} \mathbf{Q}_{xz} \mathbf{A}_1 \mathbf{Q}_{zy}$$

where $\mathbf{Q}_{xz} = \sum_i \mathbf{X}_i' \mathbf{Z}_i$, $\mathbf{Q}_{zy} = \sum_i \mathbf{Z}_i' y_i$, $\mathbf{W}_1 = \mathbf{Q}_{xz} \mathbf{A}_1 \mathbf{Q}_{xz}'$ and $\mathbf{A}_1 = (\sum_i \mathbf{Z}_i' \mathbf{H}_{1i} \mathbf{Z}_i)^{-1}$. Furthermore $\mathbf{H}_{1i}$ is defined as a diagonal matrix product of its first difference transformation and the identity matrix (Vigne, 2017; Stata Corporation, 2017).

The two step estimates of β are obtained in a similar fashion

$$(5.47) \quad \hat{\beta}_2 = \mathbf{W}_2^{-1} \mathbf{Q}_{xz} \mathbf{A}_2 \mathbf{Q}_{zy}$$

where $\mathbf{W}_2 = \mathbf{Q}_{xy} \mathbf{A}_2 \mathbf{Q}_{xz}'$ and $\mathbf{A}_2 = (\sum_i \mathbf{Z}_i' \mathbf{H}_{2i} \mathbf{Z}_i)^{-1}$. Furthermore, $\mathbf{H}_{2i}$ is a product of the one-step residuals defined as $\mathbf{H}_{2i} = \varepsilon_{1i}' \varepsilon_{1i}$

For further information about the methodology and to understand the mathematical derivation of for example the Windmeijer small sample correction it is recommended to read Stata Corporation (2017) and Windmeijer (2005).

5.3.4 Bias Corrected Least Square Dummy Variable Approach

The last dynamic panel data model that will be discussed in the course of this thesis is the *Bias Corrected Least Square Dummy Variable Approach* (LSDVC). This approach tries to tackle the inconsistencies of estimators in a dynamic panel data model with large N and finite T , the issue of which was first discovered by Nickell (1981). The advantage of the LSDVC method compared to the previously

described GMM approaches is that it also provides reliable estimates for a panel with a small sample size (Bruno, 2005b) and ensures consistency when the number of panels increases towards infinity.

To start with the LSDVC approach, when observations are collected Equation 5.38 can formally be rewritten in the following matrix format

$$(5.48) \quad y = D\eta + W\delta + \epsilon$$

where y and $W = (y_{t-1}:X)$ are $(NT \times 1)$ and $(NT \times k)$ matrices of stacked observations Bruno (2005b). Hence, W does not only represent the exogenous variables but also the lagged dependent variables included in the model. $D = I_N \otimes \iota_T$ denotes the individual dummy variables and incorporates the form of a $(NT \times N)$ matrix. Thereby, it should be noted that ι_T is the $(T \times 1)$ vector of all unity elements (Bruno, 2005b). Lastly, η and $\delta = (\alpha:\beta')$ are the vectors containing the estimated parameters, where η is a $(N \times 1)$ vector of the individual effects and $\delta = (\alpha:\beta')$ a $(k \times 1)$ vector of the coefficients. ϵ as always represents the $(NT \times 1)$ vector of error terms (Bruno, 2005b).

The LSDVC approach that is considered in this dissertation was developed by Bruno (2005a) and builds on the work of Kiviet (1999) and Bun and Kiviet (2003). In particular, it extends the LSDVC models in the regard that it also allows to process unbalanced panels, which is a requirement for the analysis in Chapter 8. To be able to also process an unbalanced panel, Bruno (2005a) developed a more general version of Equation 5.38 compared to Bun and Kiviet (2003), which does not require such a strict exogenous selection rule and allows for missing observations in the interval $[0, T]$. To derive such a model Bruno (2005a) initially defined a selection indicator r_{it} such that $r_{it} = 1$ if (y_{it}, x_{it}) is observed and $r_{it} = 0$ otherwise. Using this selection indicator, a dynamic selection rule $s(r_{it}, r_{i,t-1})$ can be obtained, the purpose of which is to select only the observations where current and one-time lagged values are observable (Bruno, 2005a). In econometric terms this can be defined as follows

$$(5.49) \quad s_{it} = \begin{cases} 1 & \text{if } (r_{i,t}, r_{i,t-1}) = (1, 1) \\ 0 & \text{otherwise} \end{cases} \quad i = 1, \dots, N \text{ and } t = 1, \dots, T$$

Thus, the number of usable observations for any i is determined by $T_i = \sum_{t=1}^T s_{it}$. Consequently, the total number of usable observations in the sample is given by

$n = \sum_{i=1}^N T_i$. The average group size of observations in the panels can be denoted by $\bar{T} = \frac{n}{N}$. Based on the outcomes of the dynamic selection rule, for each i the $(T \times 1)$ vector $s_i = [s_{i1}, \dots, s_{iT}]'$ and $(T \times T)$ diagonal matrix S_i with vector S_i on its diagonal can be defined in a next step (Bruno, 2005b). Moreover, Bruno (2005b) defines a block-diagonal matrix $S = \text{diag}(S_i)$ with a matrix form of $(NT \times NT)$, so that the unbalanced dynamic model 5.48 can be rewritten as (Bruno, 2005b):

$$(5.50) \quad Sy = SD\eta + SW\delta + S\epsilon$$

The LSDVC estimator is given by:

$$(5.51) \quad \delta_{\text{LSDV}} = (W'M_s W)^{-1} W'M_s y$$

where $M_s = S\{I - D(D'SD)^{-1}D'\}S$ is the symmetric and idempotent $(NT \times NT)$ matrix. This matrix is supposed to eliminate individual means and select usable observations (Bruno, 2005b).

DOES ENVIRONMENTAL AWARENESS FUEL THE ELECTRIC VEHICLE MARKET?

Is the purchase of an EV predominantly driven by altruistic factors? This chapter is dedicated to investigating the underlying thesis of this research, established in Chapter 3.4.1.4, that the desire to mitigate CO_2 emissions is one of the crucial determinants of the EV market. Based on a Twitter keyword as well as a Google Trends analysis, this chapter will answer the question whether a society's EA level has a significant influence on EV adoption. Therefore, statistical approaches are selected that can process a panel data set, which comprises 8 years of annual observations for 29 countries. These 29 countries are represented by EU and EFTA member states.

The results of the panel data regressions are contradictory to the outcomes of previous research that has focused on the influence of EA on the intention to adopt EVs. The baseline analysis provides evidence that EA does not significantly influence the EV market and shows that other factors play a more important role. These factors can potentially function as market barriers that first need to be overcome so that EA can become a significant determinant. The validity of the results have been verified with several robustness tests.

6.1 Twitter as an Environmental Awareness Barometer

In the first part of the analysis a Twitter keyword analysis is used to measure a society's level of EA. As pointed out in the literature review, Twitter has already been applied in related fields of research and proven its abilities as an EA barometer. Amongst other beneficial properties of Twitter for this investigation, the correlation between newspaper coverage and Tweets as well as the development that journalists are increasingly using Twitter to source information is of crucial importance. It allows the conclusion that at least to a certain degree Twitter captures the news coverage of mainstream media, from which the public also receives information and develops awareness. In contrast to newspapers, Twitter as an EA barometer, however, does not only capture the aspect of how often the public is confronted with a certain topic but also how often the public actively communicates it.

6.1.1 Descriptive Statistics

To obtain first insights about the variables considered in this investigation, descriptive statistics have been executed. These descriptive statistics encompass the mean, standard deviation, minimum and maximum of the respective variables. Furthermore, the number of observations, entities and time periods are illustrated in Table 6.1. Solely based on these seven properties of the variables, important assumptions can be made when selecting the appropriate statistical model to answer the research question. First of all, the maximum of observations of the analysis can be derived from the column *Observations*. A panel data set with 232 observations is considered to be relatively small. Secondly, the number of entities is greater than the number of time periods, which is commonly referred to as a micro panel data set. Considering only these properties, it can be concluded that a statistical approach has to be selected that can process a small panel data set with more entities than time periods.

Analysing mean, standard deviation, minimum and maximum of the variables other important properties become evident. Starting with the dependent variable, the data set exhibits a large range of EV registration rates. While on the one hand a minimum value of 0 implies that at least in one country at one point in time not a single EV was registered, on the other hand a maximum of 0.39 shows that

6.1. TWITTER AS AN ENVIRONMENTAL AWARENESS BAROMETER

EVs also accounted for almost 40% of new registrations in one of the countries. The mean value of 0.01 indicates a closer distribution of the registration rates to the minimum. However, to provide a better overview of the development of the EV market, Figure 6.1 illustrates the new registration rate of EVs for each country over the investigated time period. From the graph it can be derived that 17 of the 29 countries do not exhibit a single registration of an EV in the first year, leading to a registration rate of 0. Furthermore, the values do not seem to be normally distributed. Based on the non-normal distribution of the variable and the commonly applied log-transformation in the previous literature, especially in Münzel et al. (2019), it was decided to take the natural logarithm of the registration rate. This, however, in turn means that ratios of 0 become missing observations. Consequently, because of this transformation, the panel becomes unbalanced. Thus, an econometric model is required that can process an unbalanced panel.

Table 6.1: Descriptive Statistics

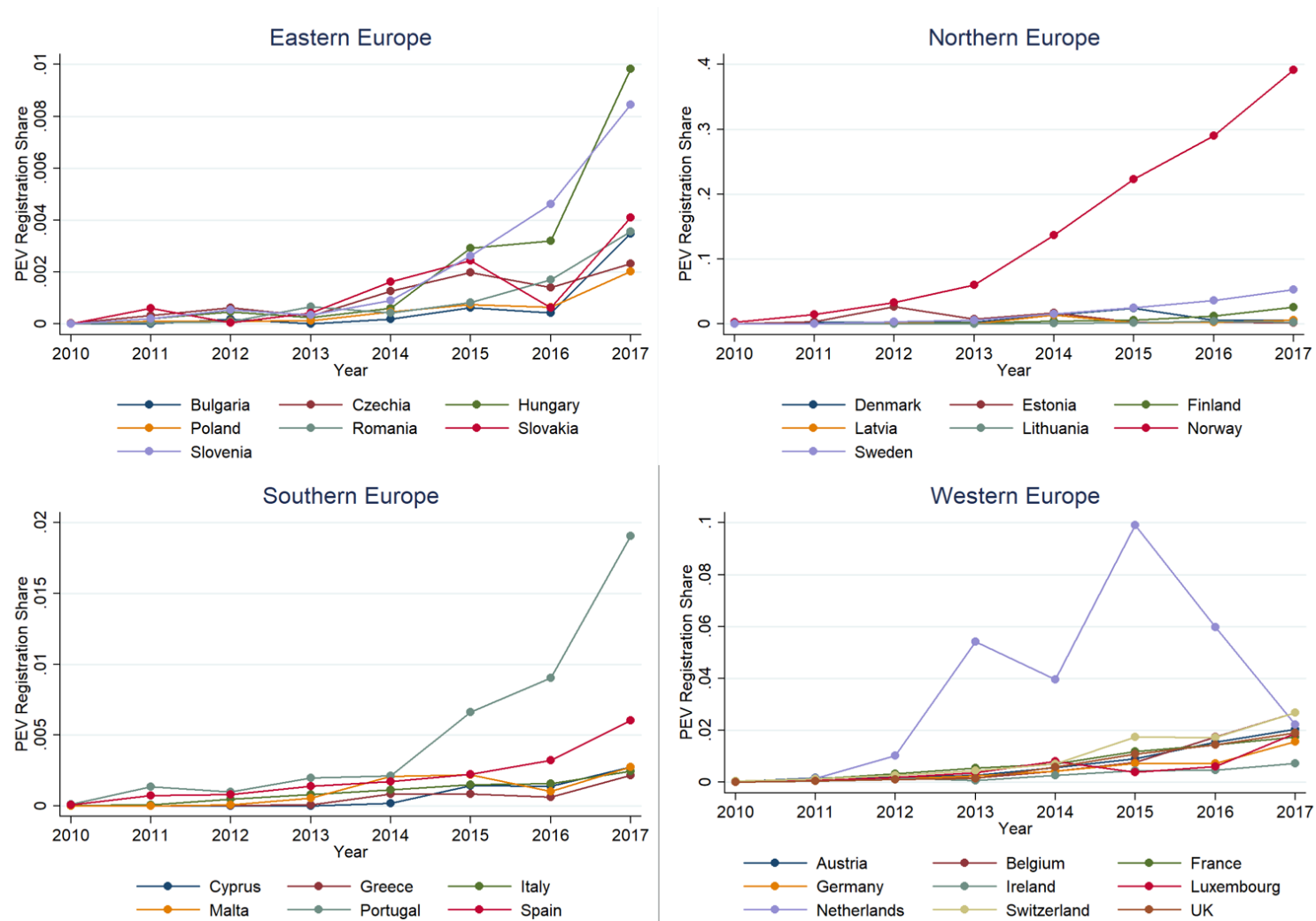
Variable		Mean	Std. Dev.	Min	Max	Observations
EV Registration Share	overall	0.0101321	0.037257	0	0.3918689	N = 232
	between		0.0267104	0.0005298	0.1442066	n = 29
	within		0.0263869	-0.1309905	0.2577943	T = 8
Environmental Awareness	overall	0.0095829	0.0088075	0.0033392	0.0316678	N = 232
	between		0	0.0095829	0.0095829	n = 29
	within		0.0088075	0.0033392	0.316678	T = 8
Charging Points	overall	1715.914	4342.442	0	33514	N = 232
	between		2947.962	9	12459.5	n = 29
	within		3229.5	-10343.59	22770.41	T = 8
Fast Chargers	overall	133.75	347.7834	0	2575	N = 232
	between		195.2117	0	740.375	n = 29
	within		289.8283	-606.625	2008.5	T = 8
Chargers per 100 km highway	overall	92.16426	234.2175	0	1966.539	N = 232
	between		201.3832	0.5738415	1052.079	n = 29
	within		124.6256	-424.3511	1006.624	T = 8
Fast Chargers per 100 km highway	overall	10.15825	34.87821	0	381.0707	N = 232
	between		22.87821	0	100.6931	n = 29
	within		25.81423	-90.34366	290.5359	T = 8
Disposable Income	overall	19409.08	5755.087	7880	33089	N = 232
	between		5741.32	9513.125	31421.63	n = 29
	within		1075.708	16754.71	22429.58	T = 8
Number EV Models	overall	40	15.87723	16	61	N = 232
	between		0	40	40	n = 29
	within		15.87723	16	61	T = 8
Electricity to Diesel Price	overall	0.0995343	0.0241047	0.0551923	0.1739604	N = 232
	between		0.0213307	0.0667116	0.1447202	n = 29
	within		0.0118248	0.072293	0.1387253	T = 8
Car Fleet	overall	8,711,060	1.21e+07	240,960	4.65e+07	N = 232
	between		1.23e+07	263,719.6	4.43e+07	n = 29
	within		493,286.8	6150,473	1.14e+07	T = 8
Subsidies	overall	3103.792	3623.263	0	15123.85	N = 232
	between		3302.193	0	13895.3	n = 29
	within		1598.122	-1798.335	8574.976	T = 8

When looking at the descriptive statistics of the main independent variable *Environmental Awareness* the only peculiarity that can be noticed is the standard deviation of 0 and the same value for the between group minimum and maximum. This is because the same observations have been used for each entity in the sample. The justification for applying the same value of EA for each country is that the reach of Twitter has no geographic borders. People can follow other people from anywhere in the world and communicate with them via Twitter. Moreover, climate change is a global threat wherefore it can be assumed that developments in the environmental awareness levels are similar in a globalised world.

The two variables representing the charging infrastructure of the countries also exhibit observations with values of 0 indicating that the charging infrastructure has just started to evolve within this time period. A household's disposable income has been considered in this investigation to account for the differing living conditions and in particular the purchasing power of the average households between the countries. This is especially important as EVs are in general more expensive than comparable ICCs and therefore, countries with a wealthier population are more likely to be able to purchase an EV. Consequently, the focus of this variable should be laid on the standard deviation around the mean. A standard deviation of 5,755.087 is considerably high when putting it into relation to the mean value of 19,409.08. This implies the existence of a large dispersion in wealth of the considered countries. Another measure that supports this assumption is the minimum and maximum value of the between estimation. The minimum value shows the average wealth of the country with the lowest disposable income over the investigated time period and the maximum for the country with the highest disposable income, respectively. A difference of more than 20,000EUR between Bulgaria, the country with the lowest disposable income, and Luxembourg, the country with the highest disposable income, can be considered to be substantial. For the number of available EV models it can only be noticed that they have strongly increased over the investigated time period. While the minimum represents the first year's observation the maximum shows the number of EV models available in Europe in 2017. The benefit of incorporating the electricity price and diesel price as a ratio is that it saves one degree of freedom in the subsequent regression. Furthermore, it directly puts into relation the fuel costs of the vehicle types. Thereby, theoretically, the lower the value of the ratio, the higher the sales of EVs, as the operation costs of EVs compared to ICCs become lower. A country's car fleet is

considered in the investigation to account for the general automobile market in the respective countries. Derived from the minimum, maximum and standard deviation it can be seen that the automobile markets significantly differ. Interestingly, the subsidies in this investigation fall in a range between 0 € and 15,123.85 € with a mean value 3,103.79 €. This means that the amount of subsidies granted by the governments strongly differs between countries and over time. Taking the mean value into consideration most of the observations are closer to the minimum than maximum of granted subsidies. Moreover, when looking at the between minimum, it can be concluded that at least one country did not grant any subsidies over the investigated time period.

Figure 6.1: EV Registration Rate 2010-2017



6.1.2 Pooled OLS

Initially a pooled OLS with robust standard errors, to account for possible misspecification, is performed to obtain first insights about the variables.

Table 6.2: Regression Results: Pooled OLS

Variable	Marginal Effects	Robust Std. Err.
Environmental Awareness	-100%***	8.40583
Chargers per 100km highway	0.1592%***	0.00055
Fast Chargers per 100km highway	0.2963%	0.00481
Disposable Income	0.0146%***	0.00001
Number EV Models	6.0279%***	0.00464
LN(Electricity to Diesel Price)	-0.7843%***	0.35834
Car Fleet	-1.6E-06%***	0.00000
Subsidies	0.0072%***	0.00002
Observations	209	
F-score	80.56***	
Overall R^2	0.7776	

Note: Pooled OLS model with robust standard errors.

The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** p < 0.01

** p < 0.05

* p < 0.1

An F-score of 80.56 and an R^2 of 0.7776 indicate an overall good data fit of the model. Further, the selection of the determinants seem to be appropriate when looking at the significance of the variables. Apart from the determinant reflecting the fast charging infrastructure all variables are significant. Moreover, most of the variables are significant at a 1% level with only the determinant accounting for the fuel prices being significant at a 5% level. However, when looking more closely at the coefficient of the main independent variable of this investigation, a negative sign contradicts the hypothesised positive relationship between EA and the EV market.

Before diving too deep into the analysis of this negative coefficient it should first be tested whether a pooled OLS is the correct specification for the data set at hand. Since the data is available in form of a panel, it is not unlikely that specific panel data models are better suited for the analysis. Hence in the following section it is checked whether panel data models are more suitable for the analysis.

6.1.3 Model Specification

Three different linear regression models are commonly applied to a panel data set. The first one in form of a pooled OLS, which was applied in the previous section, is recommended to be used if the sample consists of different entities for each

time observation in the panel (Wooldridge, 2010). In case the considered entities do not vary over time it is more likely that a fixed effects (FE) or random effects (RE) model is more appropriate for the analysis. The suitability of the different specifications can however also formally be tested. These testing procedures take place in the following. Moreover, to prevent a potential influence of model biases on the results the Gauss-Markov OLS assumptions will be tested as well.

6.1.3.1 Fixed Effects vs. Random Effects Model

To determine whether a pooled OLS is the correctly specified model, several specification tests must be executed. A first assessment to check for the poolability of the data can be made with the help of an F-test. The result of the F-test reported in Table 6.3, is a highly significant p-value suggesting the rejection of the Null-hypothesis of data poolability and favours the use of an FE model. A pooled OLS can further be rejected as the appropriate model for the data set by means of a Breusch and Pagan (1979) Lagrange multiplier test for random effects (see Table 6.4). The significance of this test indicates that rather a random effects than a pooled OLS should be applied.

Table 6.3: F-Test

F-Test	
F	F(28, 172) = 6.82
Prob >F	0.0000

Table 6.4: Breusch and Pagan Lagrange Multiplier Test for Random Effects

	Var	sd = sqrt (Var)
ln(EV sales share)	3.436144	1.853684
e	0.4380921	0.6618852
u	0.2522224	0.5022175
	$\bar{\chi}^2 (1)$	62.32
	Prob > $\bar{\chi}^2$	0.0000

After ruling out that a pooled OLS is the appropriate specification for the data set, it has to be determined whether the coefficients should be estimated by means of an FE or RE specification. For this purpose, initially a Hausman (1978) test was executed. This test exhibited a p-value of 0.7798, wherefore the Null-hypothesis of same coefficients fails to be rejected. Consequently, according to the Hausman (1978) test, an RE model would be the preferential model. However, as later found out, the residuals of the model exhibit heteroskedasticity and therefore, compromise

the reliability of the Hausman (1978) test. As suggested by Wooldridge (2010), an auxiliary regression was employed as a specification test instead. The auxiliary regression shows a significant p-value at a 1% level, implying that a FE model provides the best data fit.

Table 6.5: Mundlak Approach for FE vs. RE

All variables	
χ^2	$\chi^2 (8) = 54.76$
Prob > χ^2	0.0000

The deterministic specification test and therefore the selection of an FE model can further be supported by previous research and the scope of analysis. As pointed out in the literature review, the most commonly applied statistical model in this strand of literature is an FE model. This is at least partly caused by the benefits an FE model in this context provides. It for example allows to account for unobserved country specific factors. Furthermore, as the applied EA measure does not differ between countries but over time, a within estimator is a better method to investigate the main independent variable. The final model is therefore defined as follows:

$$\begin{aligned}
 (6.1) \quad \ln(EV)_{it} = & \beta_1 EA_{it} + \beta_2 CP_{it} + \beta_3 FC_{it} + \beta_4 DI_{it} + \beta_5 \ln\left(\frac{EP}{DP}\right)_{it} \\
 & + \beta_6 CF_{it} + \beta_7 EVM_{it} + \beta_8 S_{it} + \alpha_i + \epsilon_{it}
 \end{aligned}$$

where the subscripts i and t denote the country and year, respectively. The variable names are abbreviated in the equation and can be interpreted as follows: EV (EV registration share), EA (environmental awareness), CP (charging points total per 100km highway), FC (Fast chargers per 100km highway), DI (disposable income), EP (electricity price), DP (diesel price), CF (car fleet), EVM (EV models), S (Subsidies).

6.1.3.2 Gauss-Markov OLS Assumptions

Ensuring that no OLS assumption discussed in Chapter 5.1.3 is violated, tests for multicollinearity, misspecification of the model, heteroskedasticity and serial correlation were executed. Thereby, the first two assumptions are, as pointed out by Brooks (2019), not as important as the latter two. This is because the greater variation introduced by looking at different entities in a panel helps to mitigate the influence of multicollinearity and the FE specification accounts for time-invariant

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entity specific differences, minimising the possibility of biases arising from omitted variables. Since this investigation employs a similar data set as Münzel et al. (2019), the diagnostic tests are in most of the cases the same and often yield the same results.

Starting with testing for the absence of multicollinearity of the variables a correlation matrix and a variance inflation factor (VIF) test have been applied. As the correlation analysis can be considered as an ex ante and the VIF test as an ex post investigation, initially the correlation matrix of the variables will be reviewed. According to Kennedy (1985), a correlation coefficient higher than 0.8 can lead to severe multicollinearity, whereas Tabachnick (1996) claims that a correlation only higher than 0.9 can be a serious issue. Looking at the correlation matrix depicted in Table 6.6, the correlation between none of the variables exceeds the threshold of 0.9 or 0.8, respectively.

Table 6.6: Coefficient Correlation Matrix

	EA	Charging Points	Fast Chargers	Disposable Income	EV Models	$\ln \frac{Elec.}{Diesel}$	Car Fleet	Subsidies
EA	1.0000							
Charging Points	-0.0933	1.0000						
Fast Chargers	0.1380	-0.3323	1.0000					
Disposable Income	0.0929	0.0821	0.2355	1.0000				
Number EV Models	0.0240	-0.6183	0.0169	-0.6304	1.0000			
$\ln \frac{Elec.}{Diesel}$	-0.5384	0.0046	0.2432	0.2877	-0.1465	1.0000		
Car Fleet	0.1260	0.3584	-0.3258	-0.5330	-0.0895	-0.5252	1.0000	
Subsidies	-0.0538	0.2727	-0.1910	-0.4141	0.0116	-0.0962	0.3944	1.0000

To verify the findings from the coefficient correlation table and the absence of multicollinearity in the model, a VIF test has also been executed and the results are reported in Table 6.7. The results of the VIF test show that no variable exceeds the critical values of 10 or 5, respectively (Brooks, 2019). Consequently, the presence of multicollinearity between the variables can be ruled out.

Table 6.7: VIF Test

Variable	VIF	1/VIF
Charging Points per 100km highway	2.69	0.372158
Fast Chargers per 100km highway	2.26	0.441718
Disposable Income	1.64	0.608393
Electricity to Diesel Price	1.46	0.684768
Number EV Models	1.28	0.779066
Subsidies	1.26	0.792432
Environmental Awareness	1.22	0.822364
Car Fleet	1.11	0.903249
Mean VIF	1.62	

To check whether the regression has been correctly specified, a Ramsey RESET test is executed. For this analysis predicted values of the dependent variables of powers 2, 3 and 4 are added to the regression to check for the linearity assumption of the model. An insignificant p-value of the test, which can be seen in Table 6.8, indicates that the regression is correctly specified and the idiosyncratic errors are exogenous.

Table 6.8: Ramsey RESET Test

	RR-Test
F-score	$F(3, 28) = 0.27$
Prob >F	0.8497

Testing for heteroskedasticity in the model, a visual analysis in form of a graph that plots the residuals of the model against the fitted values is initially applied and can be seen in Figure 6.2. The outliers at the top of the graph are a first indicator for the presence of heteroskedasticity in the residuals. To formally check this presumption, a likelihood ratio test is executed as a diagnostic test (see Table 6.9). The significance of the test verifies the visual analysis of heteroskedasticity in the errors.

Figure 6.2: Heteroskedasticity

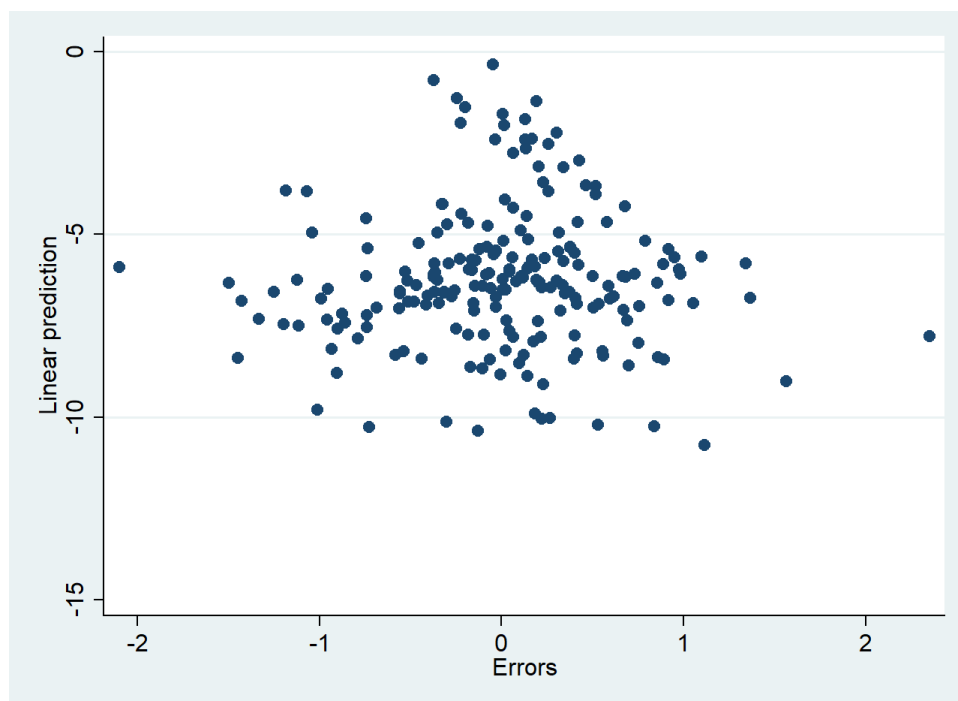


Table 6.9: Likelihood Ratio Test

Likelihood Ratio	
χ^2	$\chi^2 (28) = 120.48$
Prob > χ^2	0.0000

Finally, the idiosyncratic errors need to be checked for serial correlation. Therefore, the approach of Wooldridge (2010) is followed as it is considered an appropriate diagnostic test for one-way FE models. The significance of the test at a 1% level indicates the presence of serial correlation in the error terms (see Table 6.10).

Table 6.10: Wooldridge Test for Autocorrelation

Wooldridge	
F	$F(1, 28) = 12.180$
Prob > F	0.0016

To account for the potential influences of heteroskedasticity and serial correlation, robust standard errors clustered at country level are employed. This approach is suggested by literature to counteract these issues when having a large N and small T panel (Arellano, 1987; White, 1980). The presence of serial correlation in the idiosyncratic errors and the relatively small sample of our analysis suggest a higher validity of estimates stemming from an FE than those stemming from an first difference (FD) regression (Wooldridge, 2016; Münzel et al., 2019).

6.1.4 Results

The results of the FE panel data regression and the corresponding SEs are depicted in the first two columns of Table 6.11. Although, the results of the FE model are assumed to have a higher validity, the results and SEs of the FD model are also reported in column 3 and 4.

Table 6.11: Regression Results: 2010 - 2017

Variable	Fixed Effects		First Differences	
	Marginal Effects	Robust Std. Err.	Marginal Effects	Robust Std. Err.
Environmental Awareness	-100%***	7.47411	-100%***	7.816265
Chargers per 100km highway	-0.0286%	0.00020	-0.1397%	0.00085
Fast Chargers per 100km highway	-0.0215%	0.00103	0.5024%	0.00382
Disposable Income	0.0103%	0.00011	0.0327%***	0.00009
Number EV Models	7.5085%***	0.00668	6.8916%***	0.00917
LN(Electricity to Diesel Price)	-1.1172%	0.81077	-1.4883%**	0.70631
Car Fleet	0.0000%	0.00000	0.00%	0.00000
Subsidies	0.0097%***	0.00002	0.0078%***	0.00002
Observations	209		179	
F-score	118.50***		73.86***	
Within R^2	0.8296			
Between R^2	0.0131			
Overall R^2	0.2673		0.5369	

Note: Country Fixed Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** $p < 0.01$

** $p < 0.05$

* $p < 0.1$

After running the regression with the time horizon from 2010 to 2017, the coefficient of the main independent variable EA of the model indicates a negative influence of the EA level on the sales of EVs. This contradicts the theory, and therefore Hypothesis 3.1, that EA has a positive influence on the number of sales. When investigating the data set to find a possible explanation for this phenomenon, it becomes clear that this can most likely be attributed to the EA outlier in 2010. 2010 exhibits by far the highest value for EA (3.17%), while simultaneously exhibiting the lowest number of new EV registrations. A potential explanation for the high EA value in 2010 could be the high number of global disasters and resulting fatalities in this year. Several scholars have identified a correlation between the number of global natural disasters and tweets about environmental topics (Molodtsova et al., 2013; Cody et al., 2015) which confirms this observation. Furthermore, an analysis of the correlation between the EA determinant, the number of global disasters (Statista, 2020) and the amount of fatalities (Ritchie and Roser, 2020) as a result of natural disasters takes place. Although there are only a few observations, the correlation test (see Table 6.12) indicates an almost perfect correlation between EA

and fatalities. Therefore, it can be assumed that EA increases in times of increased natural disasters, as climate change shifts more into focus due to media reports. When investigating the EV market and the corresponding infrastructure, which existing research has shown to have a significant influence on EV sales, it becomes clear that in 2010 the infrastructure, e.g. charging station network, was not very well developed and largely even non-existent (only Norway and the Netherlands had charging points). In addition, PHEVs which do not only rely on electricity by also incorporating an internal combustion motor were no real alternative as there was only one model available on the European market. Due to these facts and the on average significantly higher prices of EVs compared to ICCs, it can be assumed that even for environmentally aware people, EVs represented no real substitute for ICCs. Consequently, another regression omitting the year 2010 while keeping everything else the same is run and the results are presented in the next section.

Table 6.12: Correlation EA & Disasters

	Environmental Awareness	Global Disasters	Fatalities
Environmental Awareness	1.0000		
Global Disasters	0.7734	1.0000	
Fatalities	0.9528	0.7151	1.0000

6.1.5 Results Environmental Awareness 2011-2017

All specification as well as assumption tests, that have been discussed in the previous subsection, are also executed with the new time-frame. However, first of all a pooled OLS with robust standard errors is again performed to obtain insights about the variables and assess whether potential changes have occurred.

As it can be seen in Table 6.13, the F-score and R^2 have slightly deteriorated, implying that the model has lost explanatory power. This can however, be traced backed to the fewer observations in this regression. A significant F-score and an R^2 value of 0.7355 nevertheless indicate a relatively high explanatory power of this model. Analysing the significance of the variables of this model, most of them have not changed their level of significance. In contrast to the first pooled OLS, the main independent variable EA now turns out to be an insignificant determinant and the coefficient is positive when omitting the year 2010.

Table 6.13: Regression Results: Pooled OLS

Variable	Marginal Effects	Robust Std. Err.
Environmental Awareness	57.4436%	22.68919
Chargers per 100km highway	0.1425%***	0.00054
Fast Chargers per 100km highway	0.3783%	0.00473
Disposable Income	0.0145%***	0.00001
Number EV Models	5.3852%***	0.00559
LN(Electricity to Diesel Price)	-0.9085%**	0.36449
Car Fleet	-1.3E-06%***	0.00000
Subsidies	0.0078%***	0.00002
Observations	193	
F-score	48.94***	
Overall R^2	0.7355	

Note: Pooled OLS model with robust standard errors.

The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** $p < 0.01$

** $p < 0.05$

* $p < 0.1$

Although, an R^2 value of 0.7355 indicates a relatively high explanatory power of the pooled OLS model, the same specification tests as in the previous section are executed with the aim of finding the most accurate model. A significant F-test as well as the Breusch and Pagan (1979) Lagrange multiplier test (see 6.15) reject the poolability of the data. An auxiliary regression further indicates that an FE model provides the best data fit. Consequently, the final model specification is in line with previous research, the scope of analysis as well as the properties of the model covering the years 2010-2017.

Table 6.14: F-Test

F-test	
F	F(28, 156) = 7.04
Prob >F	0.0000

Table 6.15: Breusch and Pagan Lagrange Multiplier Test for Random Effects

	Var	sd = sqrt (Var)
ln(EV registration share)	2.882273	1.697726
e	0.4146063	0.6438993
u	0.3472304	0.5892626
	$\bar{\chi}^2 (1)$	64.20
	Prob $> \bar{\chi}^2$	0.0000

Table 6.16: Mundlak Approach for FE vs. RE

All variables	
χ^2	$\chi^2 (8) = 59.47$
Prob $> \bar{\chi}^2$	0.0000

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In the next stage, it has to be determined whether the OLS assumptions are being met by the model. The presence of possible multicollinearity between the explanatory variables was again rejected with the help of a correlation analysis (Table 6.17) and a VIF test.

Table 6.17: Coefficient Correlation Matrix

	EA	Charging Points	Fast Chargers	Disposable Income	EV Models	$\ln \frac{Elec.}{Diesel}$	Car Fleet	Subsidies
EA	1.0000							
Chargers	0.0294	1.0000						
Fast Chargers	-0.0302	-0.4273	1.0000					
Disposable Income	-0.2218	0.4033	0.0325	1.0000				
Number EV Models	-0.2943	-0.7170	0.2622	-0.6372	1.0000			
$\ln \frac{Elec.}{Diesel}$	-0.5595	-0.1526	0.0572	0.3800	-0.1431	1.0000		
Car Fleet	0.4553	0.0946	-0.2767	-0.5732	-0.0461	-0.5858	1.0000	
Subsidies	0.3273	0.0625	-0.2377	-0.2479	-0.2261	-0.1695	0.4263	1.0000

Table 6.18: VIF Test

Variable	VIF	1/VIF
Chargers per 100km highway	2.74	0.365008
Fast Chargers per 100km highway	2.31	0.433443
Disposable Income	1.67	0.598718
Electricity to Diesel Price	1.47	0.678730
Number EV Models	1.40	0.715945
Environmental Awareness	1.34	0.743636
Subsidies	1.28	0.783010
Car Fleet	1.11	0.903862
Mean VIF	1.66	

An insignificant Ramsey RESET test indicates that the regression is not misspecified (see Table 6.19). Furthermore, a visual analysis of the residual plot (see Figure 6.3) as well as a likelihood-ratio test (see Table 6.20) show heteroskedasticity in the residuals. Lastly, the existence of serial correlation was again proven with the approach of Wooldridge (2010) (see Table 6.21). Although, the test results provide no evidence of serial correlation at a 1% level, the Null-hypothesis of no serial correlation can be rejected at a 5% level. Consequently, an FE model with robust SEs clustered at country level also seems to be the appropriate estimator for the time frame 2011 to 2017.

Table 6.19: Ramsey RESET Test

	RR-Test
F-score	F(3, 28) = 0.16
Prob >F	0.9230

Figure 6.3: Heteroskedasticity 2011-2017

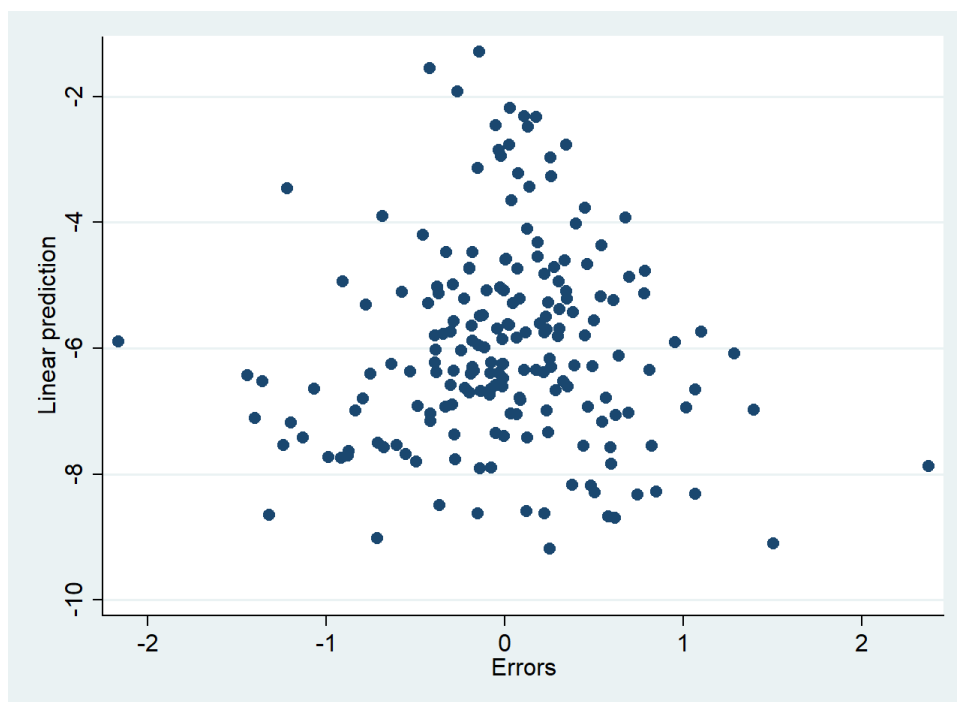


Table 6.20: Likelihood Ratio Test

Likelihood Ratio	
χ^2	$\chi^2 (28) = 143.14$
Prob > χ^2	0.0000

Table 6.21: Wooldridge Test for Autocorrelation

Wooldridge	
F	$F(1, 28) = 7.363$
Prob > F	0.0113

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Running the regression with the adjusted time frame yields the following results:

Table 6.22: Regression Results: 2011 - 2017

Variable	Fixed Effects		First Differences	
	Marginal Effects	Robust Std. Err.	Marginal Effects	Robust Std. Err.
Environmental Awareness	26,877,134%	14.54596	6473%	15.38058
Chargers per 100km highway	-0.0803%***	0.00028	-0.1244%	0.00095
Fast Chargers per 100km highway	0.1732%**	0.00068	0.5566%	0.00445
Disposable Income	0.0091%	0.00014	0.0310%***	0.00009
Number EV Models	7.1595%***	0.00842	6.5697%***	0.00920
LN(Electricity to Diesel Price)	-1.7761%**	0.81124	-2.2813%***	0.70681
Car Fleet	0.00%	0.00000	0.00%	0.00000
Subsidies	0.0112%***	0.00002	0.0076%***	0.00003
Observations	193		163	
F-score	98.90***		74.52***	
Within R^2	0.7371			
Between R^2	0.0877			
Overall R^2	0.2656		0.4087	

Note: Country Fixed Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** $p < 0.01$

** $p < 0.05$

* $p < 0.1$

An F-score of 98.90 and a within R^2 result of 0.7371 indicate a high explanatory power of the model. When analysing the significance of the variables included in the model, it can be seen that charging points total, the number of EV models and the amount of subsidies are significant at a 1% level. At a 5% level, the number of fast chargers and the ratio of electricity to diesel price exhibit a significant coefficient. Most importantly, the main independent variable EA exhibits no significant influence on the new registrations of EVs.

In the last section of this chapter a discussion of the results will take place. Thereby, different explanations for this outcome and its implications for the EV market will be presented. Furthermore, the limitations of this study will be outlined and suggestions for further research provided. However, before, an interpretation of the results takes place, the validity will be checked with several robustness tests as well as a different measure of EA.

6.1.6 Robustness Tests

The baseline results exhibit a non significant influence of EA on the registration rate of EVs. To test the validity of the results several robustness tests will be executed. These encompass a stepwise dropping of each country, the removal of small car markets from the regression, including a trend variable as well as executing an RE model. Lastly, three regressions are run that should check the robustness of the results in case of potential endogeneity or multicollinearity between the charging infrastructure variables.

6.1.6.1 Stepwise Country Exclusion

The first robustness test in this investigation is the stepwise exclusion of each country. A stepwise exclusion of each country is executed to eliminate the possibility that for example outliers in a single country too strongly influence the results of the regression. Based on the results of the regressions, which can be seen in Table 6.23, no strong deviations from the baseline results can be noticed. EA as the focus variable in this investigation remains insignificant for all alternatives.

Table 6.23: Regression Results: Stepwise Country Exclusion

Variable	Austria	Belgium	Bulgaria	Cyprus	Czechia	Denmark	Estonia	Finland	France
Environmental Awareness	7.90E+06%	4.49E+09%	2.29E+10%	3.17E+05%	5.91E+06%	1.78E+06%	1.62E+04%	4.98E+08%	1.47E+07%
Chargers per 100km highway	-0.0815%***	-0.0804%***	-0.0839%***	-0.0764%***	-0.0887%***	-0.0797%**	-0.0821%***	-0.0736%**	-0.0779%**
Fast Chargers per 100km highway	0.1703%**	0.1870%***	0.1824%***	0.1670%**	0.1835%**	0.1750%**	0.2399%***	0.1614%**	0.1621%**
Disposable Income	0.0094%	0.0081%	0.0086%	0.0066%	0.0104%	0.0111%	0.0198%**	0.0091%	0.0089%
Number EV Models	7.2744%***	7.0142%***	7.1971%***	7.2078%***	7.2810%***	7.3692%***	6.9150%***	6.9555%***	7.2095%***
LN(Electricity to Diesel Price)	-1.827%**	-1.966%**	-2.030%**	-1.599%*	-1.815%**	-1.935%**	-1.129%*	-1.734%**	-1.753%**
Car Fleet	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%
Subsidies	0.0144%***	0.0122%***	0.0111%***	0.0113%***	0.0109%***	0.0103%***	0.0103%***	0.0112%***	0.0114%***
Variable	Germany	Greece	Hungary	Ireland	Italy	Latvia	Lithuania	Luxembourg	Malta
Environmental Awareness	2.55E+07%	7.08E+08%	5.87E+06%	8.33E+06%	5.61E+07%	1.53E+07%	2.41E+06%	4.12E+08%	8.93E+07%
Chargers per 100km highway	-0.0769%**	-0.0657%**	-0.0840%**	-0.0832%***	-0.0781%**	-0.0770%***	-0.0799%***	-0.0809%***	-0.0877%***
Fast Chargers per 100km highway	0.1611%**	0.1589%**	0.1825%**	0.1692%**	0.1719%**	0.1642%**	0.1757%**	0.1827%***	0.2009%***
Disposable Income	0.0096%	0.0142%	0.0085%	0.0055%	0.0107%	0.0095%	0.0080%	0.0090%	0.0047%
Number EV Models	7.0694%***	6.5811%***	7.3338%***	7.4298%***	6.9918%***	7.0479%***	7.2181%***	7.1037%***	7.3201%***
LN(Electricity to Diesel Price)	-1.749%**	-1.983%**	-1.941%**	-1.653%*	-1.744%**	-1.549%*	-1.831%**	-1.773%**	-1.653%*
Car Fleet	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%
Subsidies	0.0115%***	0.0121%***	0.0105%***	0.0120%***	0.0114%***	0.0113%***	0.0112%***	0.0109%***	0.0113%***
Variable	Netherlands	Norway	Poland	Portugal	Romania	Slovakia	Slovenia	Spain	Sweden
Environmental Awareness	4.38E+07%	2.84E+07%	3.78E+06%	9.60E+06%	3.66E+09%	8.68E+05%	5.78E+06%	3.96E+07%	1.68E+07%
Chargers per 100km highway	-0.0612%	-0.0917%***	-0.0830%***	-0.0816%***	-0.0786%***	-0.0850%***	-0.0806%**	-0.0803%**	-0.0727%**
Fast Chargers per 100km highway	0.1297%	-0.2676%**	0.1732%**	0.1685%**	0.1857%**	0.1772%**	0.1745%***	0.1736%**	0.1447%*
Disposable Income	0.0099%	0.0090%	0.0086%	0.0084%	0.0053%	0.0068%	0.0081%	0.0088%	0.0095%
Number EV Models	6.9672%***	7.3362%***	7.1989%***	7.2213%***	7.3152%***	7.4557%***	7.2306%***	7.1808%***	6.9866%***
LN(Electricity to Diesel Price)	-1.771%**	-1.743%**	-1.761%**	-1.684%*	-1.933%**	-1.842%*	-1.790%**	-1.787%**	-1.722%**
Car Fleet	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%
Subsidies	0.0108%***	0.0112%***	0.0111%***	0.0115%***	0.0106%***	0.0114%***	0.0107%***	0.0113%***	0.0110%***
Variable	Switzerland	UK							
Environmental Awareness	2.14E+07%	5.46E+07%							
Chargers per 100km highway	-0.0898%***	-0.0863%***							
Fast Chargers per 100km highway	0.1957%***	0.1706%**							
Disposable Income	0.0090%	0.0096%							
Number EV Models	7.1840%***	7.1788%***							
LN(Electricity to Diesel Price)	-1.865%**	-1.835%**							
Car Fleet	0.0000%	0.0000%							
Subsidies	0.0112%***	0.0113%***							

Note: Country Fixed Effects model with standard errors clustered at country level. The marginal effects of the coefficients are calculated using the following formula: $100 * (e^{\beta} - 1)$. The standard errors are available upon request.

*** p < 0.01; ** p < 0.05; * p < 0.1

6.1.6.2 Exclusion of Small Car Markets

Similar to Münzel et al. (2019), this robustness test also controls for the influence of small car markets. Since the registration of one EV has a stronger influence on the registration rate in a small car market than in a large car market, anomalies can severely bias the results. This is amplified, as in an FE model each country has an equal weighting in the estimation, wherefore the influence on value of the coefficient is independent of a country's car market. Consequently, when considering the EV market in a European context, small car markets could have a leveraging effect on the outcome. To control for this effect small car markets will be excluded as a robustness test. Small car markets in this research are defined as markets with less than 30,000 new car registrations per year. Thus a country that reports less than 30,000 car registrations in one of the considered years will be excluded from the regression. Only 4 countries exhibit registration values less than this threshold. These are: Estonia, Latvia, Lithuania and Malta. Comparing the results of the regression, which are illustrated in Table 6.24 with the baseline results, it becomes evident that the main independent variable is still insignificant. The only noticeable changes in the FE model are that the variable *LN(Electricity to Diesel Price)* becomes insignificant, while the variable *Disposable Income* turns out to be significant at a 5% level.

Table 6.24: Regression Results: Exclusion Small Car Markets

Variable	Fixed Effects		First Differences	
	Marginal Effects	Robust Std. Err.	Marginal Effects	Robust Std. Err.
Environmental Awareness	-90.83%	16.14609	-74%	19.67521
Chargers per 100km highway	-0.0917%***	0.00027	-0.1613%	0.00108
Fast Chargers per 100km highway	0.2909%***	0.00080	0.4052%	0.00275
Disposable Income	0.0192%**	0.00009	0.0371%***	0.00009
Number EV Models	6.7996%***	0.00749	6.7364%***	0.01035
LN(Electricity to Diesel Price)	-0.519%	0.58627	-1.449%**	0.72300
Car Fleet	0.00%	0.00000	0.00%	0.0000
Subsidies	0.0102%***	0.00002	0.0082%**	0.00003
Observations	169		143	
F-score	79.09***		115.27***	
Within R^2	0.8182			
Between R^2	0.6366			
Overall R^2	0.7142		0.4616	

Note: Country Fixed Effects model with standard errors clustered at country level. The marginal effects of the coefficients are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** p < 0.01

** p < 0.05

* p < 0.1

6.1.6.3 Trend Variable

Pointed out by Münzel et al. (2019) as an important determinant in the regression, a trend variable is added to the model as another robustness test. The authors justify the inclusion of a trend variable to capture general trends in the EV market such as increasing EV model availability or decreasing battery prices. Also accounting for these factors, the main regression is rerun by including a trend variable in the model. The trend variable is estimated by using the natural logarithm of the years and therefore corresponds with the approach of Münzel et al. (2019). The results of the regression can be seen in the following Table 6.25.

Table 6.25: Regression Results: Trend Variable

Variable	Fixed Effects		First Differences	
	Marginal Effects	Robust Std. Err.	Marginal Effects	Robust Std. Err.
Environmental Awareness	20,846,360%	14.2667	3,175,195%	15.31871
Chargers per 100km highway	-0.0885%***	0.00031	-0.1518%	0.00104
Fast Chargers per 100km highway	0.1750%**	0.00064	0.5352%	0.00443
Disposable Income	0.0079%	0.00014	0.0275%***	0.00009
Number EV Models	5.4249%**	0.02229	3.5193%	0.02677
LN(Electricity to Diesel Price)	-1.828%**	0.78890	-2.373%***	0.68826
Car Fleet	0.00%	0.00000	0.00%	0.00000
Subsidies	0.0108%***	0.00002	0.0070%***	0.00003
Trend	1,089.65%	335.273	13,947.2%	414.343
Observations	193		163	
F-score	85.18***		70.63***	
Within R^2	0.7381			
Between R^2	0.0824			
Overall R^2	0.2879		0.4143	

Note: Country Fixed Effects model with standard errors clustered at country level. The marginal effects of the coefficients are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** $p < 0.01$

** $p < 0.05$

* $p < 0.1$

As it can be seen in Table 6.25, the variable EA still neither exhibits significant results in the FE model nor in the FD model. Another interesting finding is that in contrast to the results of Münzel et al. (2019) the trend variable in this investigation is not significant. This can potentially be traced backed to the inclusion of a variable reflecting the available EV models in the EU, in this research. In contrast, in the study of Münzel et al. (2019), this determinant should have been absorbed by the trend variable (Münzel et al., 2019). This assumption can be supported when looking at the significance level of the variable *Number EV Models*. While this variable is significant at a 1% level in the baseline model, the variable is only significant at a 5% level when including a trend variable in the model. A possible explanation for this could be that the variable *Number EV Models* captures

large parts of the explanatory power of the trend variable. To formally test this assumption, a correlation matrix is prepared (Table 6.26) and a VIF test executed (Table 6.27).

Table 6.26: Correlation with Trend Variable

	EA	Charging Points	Fast Chargers	Disposable Income	EV Models	$\ln \frac{Elec.}{Diesel}$	Car Fleet	Subsidies	Trend
EA	1.0000								
Charging Points	-0.0701	1.0000							
Fast Chargers	0.0057	-0.3626	1.0000						
Disposable Income	-0.2705	0.4512	-0.0102	1.0000					
Number EV Models	-0.2847	0.1202	0.0354	-0.1048	1.0000				
$\ln \frac{Elec.}{Diesel}$	-0.4910	0.1375	-0.0057	0.3755	-0.1466	1.0000			
Car Fleet	0.3095	0.1863	-0.2378	-0.4995	0.3508	-0.5508	1.0000		
Subsidies	0.2071	0.1259	-0.1963	-0.2285	0.2678	-0.1887	0.4828	1.0000	
Trend	0.0236	-0.3928	0.0647	-0.1394	-0.9294	0.0840	-0.3782	-0.3395	1.0000

Table 6.27: VIF Test with Trend Variable

Variable	VIF	1/VIF
Number EV Models	42.71	0.023412
Trend	41.32	0.024204
Chargers per 100km highway	2.74	0.364979
Fast Chargers per 100km highway	2.32	0.430841
Disposable Income	1.67	0.597640
Electricity to Diesel Price	1.48	0.674977
Environmental Awareness	1.43	0.699189
Subsidies	1.28	0.780796
Car Fleet	1.11	0.903471

A high correlation coefficient of -0.9294 between the variables *Number EV Models* and the trend variable, and a VIF score of 42.71 verifies the assumption of multicollinearity. Consequently, the exclusion of a trend variable in the baseline regression seems justified.

6.1.6.4 Random Effects Model

Although, the application of an FE model was not only proven by diagnostic tests but also more importantly with the help of past literature and the scope of analysis, an RE model will be executed as a robustness test. An RE model will be carried out to account for the possibility of a misspecification of the model. As discussed in Chapter 5.2.2, an RE model requires more assumptions to be fulfilled, making an FE model an in general better suited approach. The results of the RE model are as follows:

Table 6.28: Regression Results: Random Effects Model

Variable	Random Effects		First Differences	
	Marginal Effects	Robust Std. Err.	Marginal Effects	Robust Std. Err.
Environmental Awareness	40968%	13.27924	6473%	15.38058
Chargers per 100km highway	0.0375%	0.00060	-0.1244%	0.00095
Fast Chargers per 100km highway	0.0720%	0.00269	0.5566%	0.00445
Disposable Income	0.0168%***	0.00003	0.0310%***	0.00009
Number EV Models	6.2544%***	0.00498	6.5697%***	0.00920
LN(Electricity to Diesel Price)	-1.4366%**	0.70980	-2.2813%***	0.70681
Car Fleet	0.00%	0.00000	0.00%	0.00000
Subsidies	0.0103%***	3.77E-05	0.0076%***	0.00003
Observations	193		163	
Wald χ^2 -score	758.28***		74.52*** (F-score)	
Within R^2	0.7263			
Between R^2	0.6784			
Overall R^2	0.7019		0.4087	

Note: Country Random Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** p < 0.01

** p < 0.05

* p < 0.1

As it can be seen in Table 6.28, an RE model does not yield a different result for the main independent variable. Consequently, even though there might be a small probability that the model could be misspecified, the results of this regression support the findings of the baseline regression.

6.1.6.5 Charging Infrastructure

Several researchers have raised a general concern of including charging infrastructure in an analysis on a national level, as the number and distribution of charging stations can significantly differ between regions within a country (Coffman et al., 2017; Münzel et al., 2019). Moreover, some scholars pointed out that there might be a reversed causality problem between charging infrastructure and the sales of EVs, as it could be possible that governments react to increased EV purchasing behavior by providing new charging stations (Coffman et al., 2017). Since according to Münzel et al. (2019), the allocation of charging stations is, however, considered to be based on subsidies and regulations and not sales volume of EVs, in this thesis the causality problem is also assessed to be not significant for this study. Nevertheless, by running a regression that omits the charging infrastructure determinants the small probability of endogeneity in the model is accounted for.

Furthermore, when looking at the selected variables of the regression model, it can be seen that two variables that represent the entire and fast charging infrastructure of a country have been included. Although, the absence of multicollinearity

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was checked by employing a VIF test, it should be ensured that no undetected multicollinearity affects the outcome of the results. Therefore, two more robustness tests are carried out that omit *CP* and *FC*, respectively. Running these three regressions as robustness tests, the insignificance of the regression results of the main independent variable do not change for either of these variations and thus support the findings of the main part of the analysis 6.29.

Table 6.29: Regression Results: Charging Infrastructure

Variable	w/o charger		w/o charger total		w/o charger fast	
	Marginal Effects	Robust Std. Err.	Marginal Effects	Robust Std. Err.	Marginal Effects	Robust Std. Err.
Environmental Awareness	4,707,459%	14.71651	3,985,467%	14.61279	11,117,502%	14.32748
Chargers per 100km highway					-0.0511%	0.00035
Fast Chargers per 100km highway			-0.0736%	0.00077		
Disposable Income	0.0100%	0.00013	0.0099%	0.00013	0.0093%	0.00013
Number EV Models	6.7702%***	0.00730	6.8315%***	0.00759	7.1097%***	0.00840
LN(Electricity to Diesel Price)	-1.6502%**	0.78667	-1.656%**	0.78094	-1.7399%**	0.79184
Car Fleet	0.00%	0.00000	0.00%	0.00000	0.00%	0.00000
Subsidies	0.0112%***	0.00002	0.0113%***	0.00002	0.0113%***	0.00002
Observations	193		193		193	
F-score	126.75***		107.74***		103.66***	
Within R^2	0.7342		0.7345		0.7365	
Between R^2	0.1380		0.1323		0.0978	
Overall R^2	0.2983		0.2939		0.2713	

Note: Country Fixed Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. Only Fixed Effects results are reported.

*** $p < 0.01$

** $p < 0.05$

* $p < 0.1$

6.2 Google Trends as an Environmental Awareness Barometer

It is difficult, if not impossible to develop an unbiased variable that can perfectly reflect a psychological factor such as EA. This is because psychological factors are more difficult to observe and consequently more challenging to measure. In contrast to for example the registration rate of cars, EA levels are not directly measurable and must be derived by means of appropriate surrogates. Although, Twitter is as pointed out in the literature review an appropriate and innovative source of information to measure the awareness of a society regarding a certain topic, it is not free of limitations. Therefore, in this subchapter a different measure of EA will be applied to check for the validity of the results.

Henceforth, EA will be measured using Google Trends (GT). A detailed description of the data collection approach and the properties of this variable can be

found in Chapter 4.2.1. GT is as already discussed not an uncommon measure for awareness. Vergis and Chen (2015) for example used GT to measure a society's awareness of EVs. The baseline analysis as well as all robustness tests that have been carried out in the previous section will be applied to this analysis as well to allow a comparison between the results.

6.2.1 Descriptive Statistics

To obtain first insights into the properties of the variables, descriptive statistics are executed. As all variables except EA are the same as in the previous analysis, only the descriptive statistics of the EA measure will be discussed and illustrated in table 6.30.¹

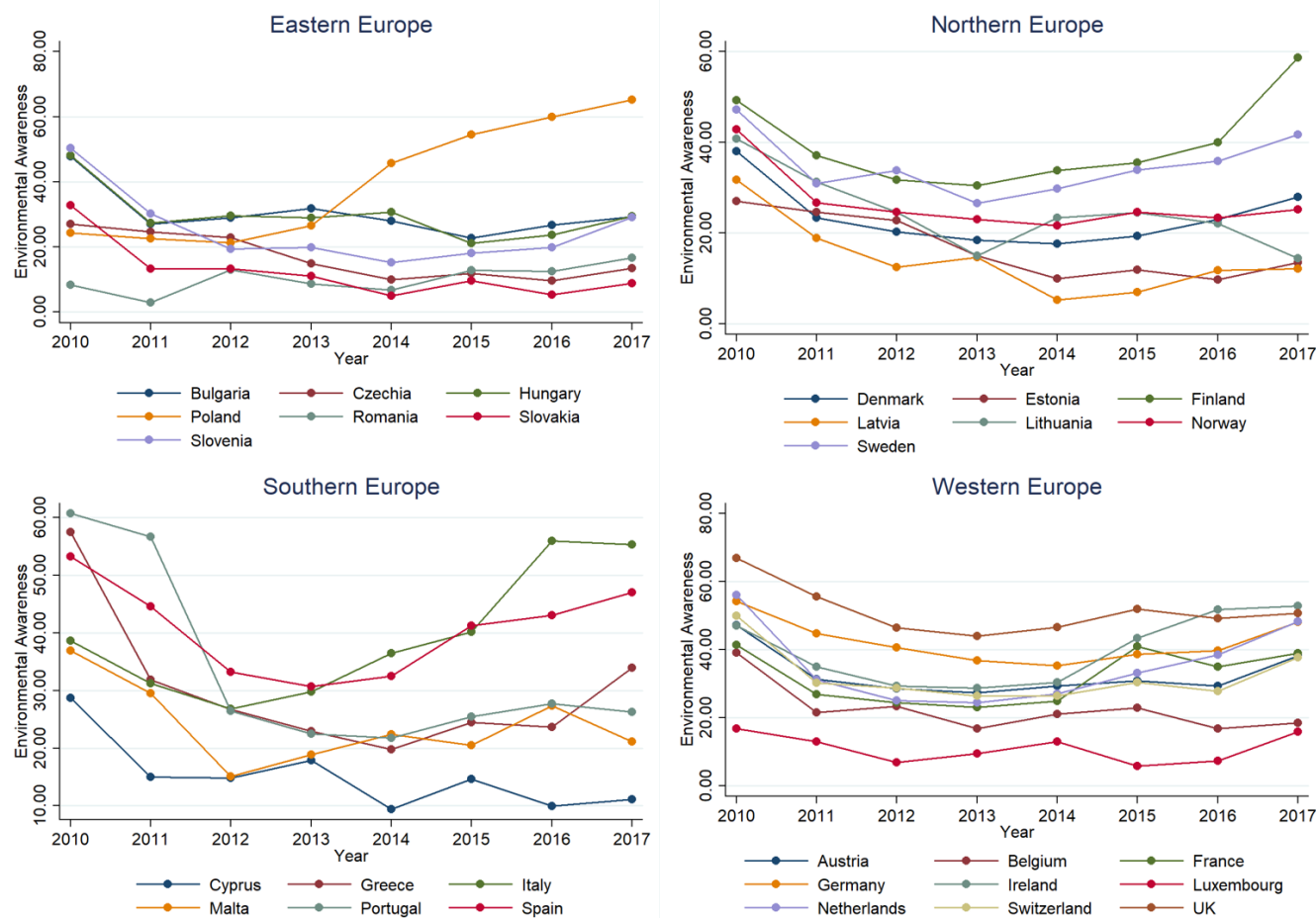
Table 6.30: Descriptive Statistics Google Trends

Variable		Mean	Std. Dev.	Min	Max	Observations
Environmental Awareness	overall	28.51311	13.52109	2.916667	66.91667	N = 232
	between		10.67781	10.23958	51.42708	n = 29
	within		8.500548	9.742277	55.83603	T = 8

To interpret the results, it is important to keep in mind that the highest value of a Google Trend index for a time series is 100 and all other values are measured in relation to this maximum. Consequently, the first peculiarity that can be seen in the descriptive statistics is that the maximum of 100 is not reported as an overall maximum value. This is because an annual average has been built from the monthly values of the corresponding years. Looking at the overall mean of 28.51, this value is relatively small. It therefore suggests that in most countries at a certain point in time an outlier with a high level of EA must have existed. However, to identify when and in which countries the increased level of EA has occurred, graphs that show the development of EA for the respective countries are illustrated in Figure 6.4. From the figure it can be seen that most countries exhibit the highest EA level in the first year. This further supports the analysis of the previous chapter that 2010 was an exceptional year and should be dropped from the investigation. The other descriptive statistics do not provide valuable new information and will, therefore, not further be discussed.

¹The descriptive statistics of the other variables can be found in table 6.1.

Figure 6.4: Environmental Awareness Level Measured with Google Trends



6.2.2 Pooled OLS

To obtain first insights about the variables and their explanatory power in a linear regression model, a classical pooled OLS regression with robust standard errors, to account for the possibility of misspecification, is executed.

Table 6.31: Regression Results: Pooled OLS

Variable	Marginal Effects	Robust Std. Err.
Environmental Awareness	-0.3789%	0.00533
Chargers per 100km highway	0.1597%***	0.00056
Fast Chargers per 100km highway	0.2219%	0.00487
Disposable Income	0.0150%***	0.00001
Number EV Models	6.8742%***	0.00487
LN(Electricity to Diesel Price)	-1.2466%***	0.38675
Car Fleet	-1.5E-06%***	0.00000
Subsidies	0.0067%***	0.00002
Observations	209	
F-score	58.61***	
Overall R^2	0.7485	

Note: Pooled OLS model with robust standard errors.

The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** $p < 0.01$

** $p < 0.05$

* $p < 0.1$

Based on the R^2 value of 0.7485, it can be concluded that the regression model exhibits a relatively high explanatory power. Furthermore, the results of the regression show that all variables, except EA and the fast charger determinant, are all highly significant at a 1% level. Moreover, 5 of the variables exhibit highly significant coefficients. Interestingly, in contrast to the pooled OLS regression of the previous chapter when considering the entire time span, the determinant EA is not significant. This provides a first indication that the results obtained under the analysis with the limited time frame are more reliable. However, as the data set is in form of a panel, it first has to be checked whether a panel data model better fits the data. Hence in the next section of this chapter the same diagnostic checks as in the previous chapter are applied.

6.2.3 Model Specification

As in the analysis where EA was measured by using Twitter, a crucial task in this section is to identify an econometric model that best fits the data so that the estimates are unbiased. Consequently, in this part of the analysis the correct panel data model specification will first be identified. Thereafter, this model is checked for potential violations of the Gauss-Markov OLS assumptions to ensure that the estimates obtained from the final regression are indeed BLUE.

6.2.3.1 Fixed Effects vs. Random Effects Model

To determine whether a fixed effects or a random effects model provides a better data fit than a pooled OLS, several diagnostic tests can be used. A first idea of whether a pooled OLS is an appropriate model can be generated when looking at the F-test. A significant F-test at a 1%, however rejects the Null-hypothesis of poolability and is a first indication that one of the other two models are more suitable. Another test that is applied to check a potential misspecification of the pooled OLS model is the Breusch and Pagan (1979) LM test. A significant p-value of this test suggests to reject the Null-hypothesis that the variance of unobserved fixed effects is 0, and therefore pooled OLS should not be applied.

Table 6.32: F-Test

F-Test	
F	F(28, 172) = 6.65
Prob >F	0.0000

Table 6.33: Breusch and Pagan Lagrange Multiplier Test for Random Effects

	Var	sd = sqrt (Var)
ln(PEV sales share)	3.436144	1.853684
e	0.5018998	0.7084489
u	0.2541819	0.5041645
	$\chi^2 (1)$	47.15
	Prob > χ^2	0.0000

The next step is to determine whether the data fits better into an RE or an FE model. The commonly applied diagnostic test to decide between an RE and an FE model would be a Hausman (1978) test. However, as in the model where EA was measured with Twitter, heteroskedasticity is also present in this model. Consequently, an auxilliary regression is performed (Wooldridge, 2010). The significant

p-value of this test, which can be seen in Table 6.34, suggests that an FE model should be preferred over an RE model.

Table 6.34: Mundlak Approach for FE vs. RE

All variables	
χ^2	$\chi^2 (8) = 63.89$
Prob > χ^2	0.0000

Furthermore, the selection of the model can again be underscored by previous research, the scope of analysis and the properties of the main independent variable. Due to the abilities of an FE model to account for time-invariant determinants, this model is able to overcome certain compromising effects. One such effect is the removal of the threat of omitted variable bias between countries. Including 29 countries in the panel, there is a substantial probability that determinants exists that can explain differences between countries but are time-invariant such as culture. Focusing on the development of variables over time, an FE model automatically controls for time-invariant factors. Considering that the main independent variable is an index measure assigning values in relation to the highest value of an entity's time series, an FE model seems to be the most appropriate as it solely focuses on the within variance in a country and neglects the variance of this factor between the countries. As the considered model has the same properties as in the previous subchapter, the model can be defined as Equation 6.1.

6.2.3.2 Gauss-Markov OLS Assumptions

Before running the regression, some other important test have to be executed to guarantee the validity of the results. These are the same tests as in the previous chapter and encompass testing for multicollinearity, misspecification of the model, heteroskedasticity and serial correlation.

The absence of multicollinearity is tested by means of a coefficient correlation matrix and a VIF test. Looking initially at the correlation matrix (Table 6.35), no serious correlation between the independent variables can be identified. The absence of multicollinearity is further supported by the VIF test (Table 6.36). No variable exhibits a VIF score that exceeds 10 or 5, respectively, which are commonly considered as the threshold values of multicollinearity (Brooks, 2019). Therefore, similar to the analysis where Twitter was used as an EA measure, there is no indication of multicollinearity between the variables in this analysis.

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Table 6.35: Coefficient Correlation Matrix

	EA	Charging Points	Fast Chargers	Disposable Income	EV Models	$\ln \frac{Elec.}{Diesel}$	Car Fleet	Subsidies
EA	1.0000							
Charging Points	-0.5023	1.0000						
Fast Chargers	0.4724	-0.5450	1.0000					
Disposable Income	-0.1873	0.1556	0.1103	1.0000				
Number EV Models	0.2145	-0.6509	0.1910	-0.6217	1.0000			
$\ln \frac{Elec.}{Diesel}$	-0.5182	0.3957	-0.1732	0.5168	-0.4162	1.0000		
Car Fleet	-0.2044	0.3807	-0.4400	-0.5400	-0.1288	-0.3296	1.0000	
Subsidies	-0.1076	0.4257	-0.3430	-0.2051	-0.3359	-0.0067	0.5294	1.0000

Table 6.36: VIF Test

Variable	VIF	1/VIF
Chargers per 100km highway	2.72	0.368188
Fast Chargers per 100km highway	2.27	0.440359
Disposable Income	1.64	0.609994
Environmental Awareness	1.51	0.662659
Car Fleet	1.45	0.687533
Electricity to Diesel Price	1.38	0.726036
Subsidies	1.28	0.781602
Number EV Models	1.16	0.863950
Mean VIF	1.68	

A Ramsey RESET test is performed to check whether the model is correctly specified. Following the approach of the Twitter analysis, predicted values of the dependent variables in form of powers of 2, 3 and 4 are added to the regression model. An insignificant p-value proves that the model is correctly specified and the inclusion of the squared dependent variable as well as higher order of powers do not provide any additional explanatory power (see Table 6.37).

Table 6.37: Ramsey RESET Test

RR-Test	
F-score	F(3, 28) = 0.35
Prob >F	0.7925

To detect the presence of heteroskedasticity, visual as well as diagnostic analyses are performed. Figure 6.5 plots the residuals against the fitted values. Outliers at the top of the graph again indicate heteroskedasticity in the residuals. This assumption has been verified by a significant likelihood ratio test, results of which are reported in Table 6.38.

Figure 6.5: Heteroskedasticity

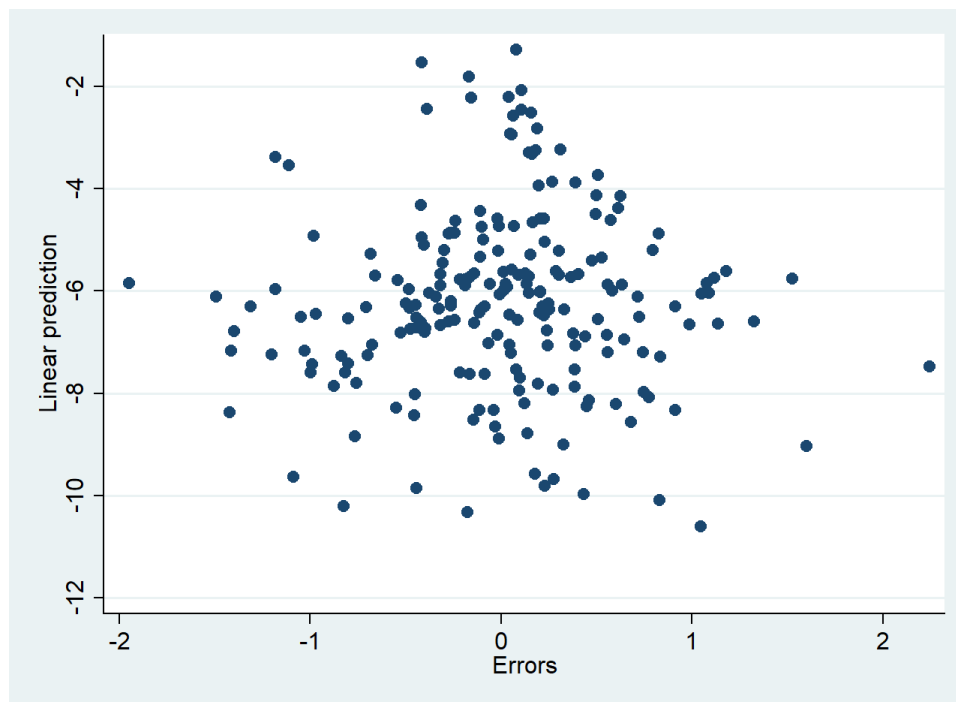


Table 6.38: Likelihood Ratio Test

Likelihood Ratio	
χ^2	$\chi^2(28) = 114$
Prob > χ^2	0.0000

Lastly, the FE regression is checked for serial correlation by following the approach of Wooldridge (2010). A test result, significant at a 1% level suggests the presence of serial correlation (see Table 6.39).

Table 6.39: Wooldridge Test for Autocorrelation

Wooldridge	
F	$F(1, 28) = 20.894$
Prob > F	0.0001

As a consequence of heteroskedasticity and serial correlation in the residuals, robust standard errors clustered at country level are employed. According to Arelano (1987) and White (1980), this is an appropriate approach when dealing with a large N and small T panel.

6.2.4 Results

Table 6.40 shows the regression results of the FE and FD models for the investigated time period 2010 to 2017. Based on the properties of the data set, it is again assumed that an FE model provides more valid estimates than an FD model.

Like the regression results in chapter 6.1.4 covering the entire time period, the coefficient for EA measured by Google Trends does exhibit a significant and negative influence on the registration rate of EVs. Furthermore, the ratio of the electricity to Diesel price, which has previously been insignificant, becomes significant at a 1% level. In addition, the determinant *Car Fleet* becomes significant at a 1% level. Apart from these changes the results of the regression using Google Trends do not strongly deviate from the former method.

Focusing, on the coefficient of the variable EA, it still exhibits a negative sign. This implies that EA has the opposite of the hypothesized influence on the EV market and therefore does not correspond with the theory. To explain this anomaly, the same limitations as before when including the year 2010 can be argued. The underdeveloped EV market as well as the high value for EA in 2010 lead to the negative relationship between this independent and the dependent variable. Consequently, to obtain comparable results but more importantly to account for these limitations, observations of the year 2010 will be dropped in the following reducing the time period to 2011 to 2017.

Table 6.40: Regression Results: 2010 - 2017

Variable	Fixed Effects		First Differences	
	Marginal Effects	Robust Std. Err.	Marginal Effects	Robust Std. Err.
Environmental Awareness	-2.0924%**	0.00913	-2.7415%***	0.00978
Chargers per 100km highway	-0.0268%	0.00031	-0.1298%*	0.00074
Fast Chargers per 100km highway	-0.0951%	0.00121	0.5027%	0.00385
Disposable Income	0.0082%	0.00012	0.0298%***	0.00010
Number EV Models	8.4220%***	0.00807	7.7467%***	0.00956
LN(Electricity to Diesel Price)	-2.5018%***	0.80035	-2.943%***	0.58996
Car Fleet	0.00%**	0.00000	0.00%	0.00000
Subsidies	0.0104%***	0.00003	0.0091%***	0.00003
Observations	209		179	
F-score	116.77***		86.29***	
Within R^2	0.8048			
Between R^2	0.0014			
Overall R^2	0.0630		0.4920	

Note: Country Fixed Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** p < 0.01

** p < 0.05

* p < 0.1

6.2.5 Results Environmental Awareness 2011-2017

To check whether an FE model with robust standard errors clustered at country level is also the appropriate model for the measurement of EA by means of Google Trends in the time period 2011-2017, all specification tests have been repeated. The first step of the investigation, however, is to run a pooled OLS to obtain first insights about the explanatory power of a linear regression. Accounting for possible misspecifications, the standard errors of the regression are specified to be robust. The results of the pooled OLS can be seen in Table 6.41. Most of the variables still exhibit coefficients at a high statistical significance level. In line with the pooled OLS performed with the complete data set, the variable EA is still not significant. Furthermore, the omission of the year 2010 has only caused a slight deterioration of the R^2 value and hence the overall explanatory power of the model.

Table 6.41: Regression Results: Pooled OLS

Variable	Marginal Effects	Robust Std. Err.
Environmental Awareness	0.7927%	0.00557
Chargers per 100km highway	0.1360**	0.00055
Fast Chargers per 100km highway	0.4132%	0.00477
Disposable Income	0.0145%***	0.00001
Number EV Models	5.3468%***	0.00508
LN(Electricity to Diesel Price)	-0.9437%***	0.35764
Car Fleet	-1.7E-06%***	0.00000
Subsidies	0.0075%***	0.00002
Observations	193	
F-score	51.82***	
Overall R^2	0.7378	

Note: Pooled OLS model with robust standard errors.
The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$
*** p < 0.01
** p < 0.05
* p < 0.1

Although, the explanatory power of the pooled OLS model is still relatively high with a value of 0.7378, in the next step it has to be determined if a pooled OLS properly fits the data. Therefore, two tests are executed. The first test is an F-test and its significant result at a 1% level suggests that the data should not be pooled (see Table 6.42). The second test that is consulted is the Breusch and Pagan (1979) LM test. The significant p-value of the test, reported in Table 6.43 recommends to use a panel data model.

Table 6.42: F-Test

F-test	
F	F(28, 156) = 7.02
Prob >F	0.0000

Table 6.43: Breusch and Pagan Lagrange Multiplier Test for Random Effects

	Var	sd = sqrt (Var)
ln(EV registration share)	2.882273	1.697726
e	0.4114636	0.6414543
u	0.3462046	0.5883915
	$\chi^2 (1)$	66.32
	Prob > χ^2	0.0000

To decide whether the data should be fitted into an FE or RE model, an auxiliary regression is used. An auxiliary regression is applied instead of a Hausman (1978) test because of the presence of heteroskedasticity in the residuals (Wooldridge, 2010). A significant auxiliary regression favors the application of an FE model over an RE model (see Table 6.44). This method can be further supported by previous research, the scope of analysis and the properties of the main independent variable, which has already been discussed in the previous chapters.

Table 6.44: Mundlak Approach for FE vs. RE

Augmented Regression	
χ^2	$\chi^2 (8) = 46.41$
Prob > χ^2	0.0000

Before running the FE model, tests to detect potential misspecifications of the model and that all OLS assumptions are met have to be performed. Testing for multicollinearity between the independent variables a coefficient correlation table is made and a VIF test is carried out. As it can be seen in Table 6.45 the coefficients of no variable pair exceeds a correlation higher than 0.8 or 0.9, respectively, indicating no severe multicollinearity between the variables. This assumption is further supported by a VIF test. No variable exceeds the threshold value of 10 or 5 as it can be seen in Table 6.46.

Table 6.45: Correlation of Coefficients

	EA	Charging Points	Fast Chargers	Disposable Income	EV Models	ln $\frac{Elec.}{Diesel}$	Car Fleet	Subsidies
EA	1.0000							
Charging Points	-0.4818	1.0000						
Fast Chargers	0.3360	-0.5928	1.0000					
Disposable Income	-0.4714	0.5401	-0.2740	1.0000				
Number EV Models	0.2917	-0.7563	0.4626	-0.6684	1.0000			
ln $\frac{Elec.}{Diesel}$	-0.4359	0.2533	-0.1463	0.3360	-0.2463	1.0000		
Car Fleet	-0.1617	0.1859	-0.2216	-0.3497	0.1355	-0.2945	1.0000	
Subsidies	0.1494	-0.0623	-0.0739	-0.2739	-0.1028	-0.0426	0.2385	1.0000

Table 6.46: VIF Test

Variable	VIF	1/VIF
Chargers per 100km highway	2.78	0.359652
Fast Chargers per 100km highway	2.33	0.428625
Disposable Income	1.66	0.600674
Environmental Awareness	1.56	0.640629
Car Fleet	1.56	0.642132
Electricity to Diesel Price	1.42	0.705691
Subsidies	1.30	0.770390
Number EV Models	1.17	0.851336
Mean VIF	1.72	

In the next step it is tested whether the dependent variable might be better explained with a non-linear combination of the independent variables and is therefore misspecified. For this purpose a Ramsey RESET test is applied. In particular powers 2,3 and 4 of the predicted dependent variable are added to the regression model (see Table 6.47). An insignificant Ramsey RESET test suggests that the model is not misspecified.

Table 6.47: Ramsey RESET Test

RR-Test	
F-score	F(3, 28) = 0.20
Prob >F	0.8934

The existence of heteroskedasticity in the residuals is tested visually and with a likelihood ratio test. The residual plot depicted in Figure 6.6 as well as the diagnostic test, results of which are reported in Table 6.48, identify heteroskedasticity in the residuals. The last step in the process is to test for serial correlation. Executing Wooldridge's 2010 test for serial correlation exhibits a significant p-value at a 1% level (see Table 6.49). Therefore, the Null-hypothesis of no first-order autocorrelation can be rejected.

Figure 6.6: Heteroskedasticity 2011-2017

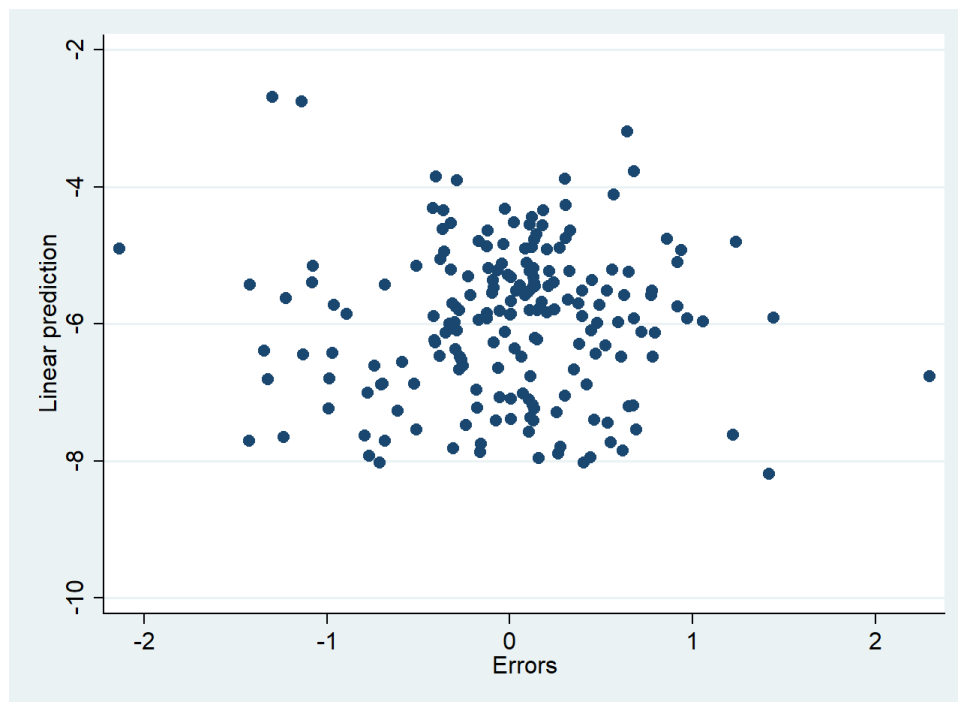


Table 6.48: Likelihood Ratio Test

Likelihood Ratio	
χ^2	$\chi^2 (28) = 141.68$
Prob > χ^2	0.0000

Table 6.49: Wooldridge Test for Autocorrelation

Wooldridge	
F	$F(1, 28) = 8.213$
Prob > F	0.0078

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Consequently, the appropriate model for the data of the investigated time period is also an FE model with robust standard errors clustered at country level. Running the model yields the following results:

Table 6.50: Regression Results: 2011 - 2017

Variable	Fixed Effects		First Differences	
	Marginal Effects	Robust Std. Err.	Marginal Effects	Robust Std. Err.
Environmental Awareness	1.022%	0.00895	-0.4871%	0.01007
Chargers per 100km highway	-0.0929%***	0.00033	-0.1229%	0.00090
Fast Chargers per 100km highway	0.2208%***	0.00071	0.5549%	0.00434
Disposable Income	0.0099%	0.00013	0.0323%***	0.00009
Number EV Models	7.2244%***	0.00784	6.4776%***	0.00933
LN(Electricity to Diesel Price)	-1.631%**	0.71990	-2.1978%***	0.61671
Car Fleet	0.00%	0.00000	0.00%	0.00000
Subsidies	0.0109%***	0.00002	0.0077%***	0.00003
Observations	193		163	
F-score	68.23***		63.36***	
Within R^2	0.7391			
Between R^2	0.3148			
Overall R^2	0.5014		0.4093	

Note: Country Fixed Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** p < 0.01

** p < 0.05

* p < 0.1

An F-score of 68.23 and a within R^2 value of 0.7391 indicate a relatively high explanatory power of the model. Looking at the significance of the determinants, both determinants representing the charging infrastructure, the number of EV models and the amount of subsidies are significant at a 1% level. Furthermore, the ratio of the fuel prices is significant at a 5%. Statistically insignificant are the average household's disposable income of a country, a country's car fleet and most importantly EA. These outcomes are in line with the previous analysis when EA was measured by a Twitter keyword analysis and further support the finding that EA is not a significant driver of the EV market. A more thorough discussion of the results will take place at the end of the chapter. Beforehand, the validity of the results will be checked by applying several robustness tests.

6.2.6 Robustness Tests

Testing the validity of the results for the measure of EA by means of Google Trends, the same robustness tests as in Chapter 6.1.6 will be executed. The observation period for all robustness tests is from 2011-2017, to ensure comparability with the results of the previous subchapter. Furthermore, the selection of the time period is to overcome the discussed limitations of the EV market.

6.2.6.1 Stepwise Country Exclusion

The first robustness test controls for the potential driving influence of a single country on the outcomes of the baseline regression. Therefore, each country is stepwise excluded from the model and the regressions are rerun. Based on the results of the regressions that can be seen in Table 6.51, the main independent variable remains insignificant for all alternatives. This rules out the possibility that one country is primarily responsible for the insignificance of this determinant.

Table 6.51: Regression Results: Stepwise Country Exclusion

Variable	Austria	Belgium	Bulgaria	Cyprus	Czechia	Denmark	Estonia	Finland	France
Environmental Awareness	1.04%	1.09%	0.94%	0.95%	0.76%	1.16%	0.35%	0.81%	1.17%
Chargers per 100km highway	-0.0944%***	-0.0932%***	-0.0936%***	-0.0890%**	-0.0965%***	-0.0946%**	-0.0864%***	-0.0832%**	-0.0916%**
Fast Chargers per 100km highway	0.2193%***	0.2351%***	0.2190%***	0.2147%***	0.2160%***	0.2318%***	0.2566%***	0.1969%**	0.2126%***
Disposable Income	0.0101%	0.0090%	0.0094%	0.0072%	0.0108%	0.0119%	0.0201%**	0.0097%	0.0097%
Number EV Models	7.3346%***	7.1028%***	7.2853%***	7.2541%***	7.3236%***	7.4192%***	6.9424%***	7.0503%***	7.2952%***
LN(Electricity to Diesel Price)	-1.7024%**	-1.7613%**	-1.7863%**	-1.5103%**	-1.6728%**	-1.8275%**	-1.0738%**	-1.5436%**	-1.6056%**
Car Fleet	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%
Subsidies	0.0112%***	0.0117%***	0.0108%***	0.0110%***	0.0107%***	0.0100%***	0.0102%***	0.0109%***	0.0112%***
Variable	Germany	Greece	Hungary	Ireland	Italy	Latvia	Lithuania	Luxembourg	Malta
Environmental Awareness	1.01%	0.96%	1.14%	1.30%	1.15%	1.18%	0.92%	1.00%	1.03%
Chargers per 100km highway	-0.0900%**	-0.0773%**	-0.0982%***	-0.1015%***	-0.0950%**	-0.0921%***	-0.0916%***	-0.0927%***	-0.1015%***
Fast Chargers per 100km highway	0.2124%**	0.2019%**	0.2377%***	0.2338%***	0.2299%***	0.2212%***	0.2194%***	0.2258%***	0.2535%***
Disposable Income	0.0101%	0.0148%	0.0093%	0.0062%	0.0107%	0.0104%	0.0087%	0.0098%	0.0059%
Number EV Models	7.1726%***	6.6824%***	7.3782%***	7.5274%***	7.1452%***	7.1078%***	7.2739%***	7.1779%***	7.3633%***
LN(Electricity to Diesel Price)	-1.6167%**	-1.8047%**	-1.8208%**	-1.5080%**	-1.5944%**	-1.4102%**	-1.7126%**	-1.5980%**	-1.4855%**
Car Fleet	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%
Subsidies	0.0111%***	0.0116%***	0.0102%***	0.0119%***	0.0109%***	0.0109%***	0.0109%***	0.0107%***	0.0109%***
Variable	Netherlands	Norway	Poland	Portugal	Romania	Slovakia	Slovenia	Spain	Sweden
Environmental Awareness	1.35%	1.03%	1.18%	0.88%	1.00%	0.96%	1.03%	1.00%	0.92%
Chargers per 100km highway	-0.0654%	-0.1056%**	-0.1010%***	-0.0907%***	-0.0900%**	-0.0963%***	-0.0934%**	-0.0928%***	-0.0841%**
Fast Chargers per 100km highway	0.1550%	-0.2203%	0.2326%***	0.2080%***	0.2266%***	0.2226%***	0.2239%***	0.2201%***	0.1892%**
Disposable Income	0.0108%	0.0096%	0.0090%	0.0093%	0.0068%	0.0078%	0.0092%	0.0096%	0.0102%
Number EV Models	7.0173%***	7.4082%***	7.2587%***	7.2400%***	7.3670%***	7.4614%***	7.2602%***	7.2467%***	7.0539%***
LN(Electricity to Diesel Price)	-1.6239%**	-1.5944%**	-1.6477%**	-1.5653%**	-1.7218%**	-1.7289%**	-1.6677%**	-1.6321%**	-1.5814%**
Car Fleet	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%
Subsidies	0.0103%***	0.0108%***	0.0108%***	0.0111%***	0.0104%***	0.0111%***	0.0104%***	0.0109%***	0.0107%***
Variable	Switzerland	UK							
Environmental Awareness	1.00%	1.35%							
Chargers per 100km highway	-0.1026%***	-0.1051%***							
Fast Chargers per 100km highway	0.2447%***	0.2320%**							
Disposable Income	0.0095%	0.0109%							
Number EV Models	7.2641%***	7.2560%***							
LN(Electricity to Diesel Price)	-1.7244%**	-1.6915%**							
Car Fleet	0.0000%	0.0000%							
Subsidies	0.0109%***	0.0109%***							

Note: Country Fixed Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. The standard errors are available upon request.

*** p < 0.01; ** p < 0.05; * p < 0.1

6.2.6.2 Exclusion of Small Car Markets

As a second robustness test, all countries with a car market smaller than 30,000 new registered cars per year are excluded from the analysis. The reason for excluding these markets is that they only contribute to a small proportion of the European automobile sector, however, due to the properties of an FE model have the same weighting as the largest automobile sectors in the EU. Therefore, it might be interesting whether EA plays a more significant role for countries with a larger vehicle market. In total 4 countries are excluded from the regression, namely Estonia, Latvia, Lithuania and Malta. The results of this robustness test can be seen in Table 6.52. As in the Chapter 6.1.6.2, excluding small car markets from the regression has not resulted in a significant influence of EA on EV registration rates.

Table 6.52: Regression Results: Exclusion Small Car Markets

Variable	Fixed Effects		First Differences	
	Marginal Effects	Robust Std. Err.	Marginal Effects	Robust Std. Err.
Environmental Awareness	0.388%	0.00814	-0.010%	0.00904
Chargers per 100km highway	-0.0976%***	0.00029	-0.1608%	0.00108
Fast Chargers per 100km highway	0.3102%***	0.00090	0.4047%	0.00276
Disposable Income	0.0192%**	0.00008	0.0369%***	0.00009
Number EV Models	6.8110%***	0.00731	6.7457%***	0.01058
LN(Electricity to Diesel Price)	-0.5812%	0.47439	-1.4805%***	0.48466
Car Fleet	0.00%	0.0000	0.00%	0.00000
Subsidies	0.0102%***	0.00002	0.0082%**	0.00003
Observations	169		143	
F-score	69.94***		114.49***	
Within R^2	0.8186			
Between R^2	0.5858			
Overall R^2	0.6850		0.67785	

Note: Country Fixed Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** $p < 0.01$

** $p < 0.05$

* $p < 0.1$

6.2.6.3 Trend Variable

Although the insignificance of a trend variable has already been elaborated in Chapter 6.1.6.3, for completeness, a robustness test including a trend variable is also performed in this model setting. The insignificant coefficient of the trend term confirms that the previous result is not driven by the measure of EA. Therefore, the inclusion of a trend variable is not necessary in this model as the variable *Number of EV Models* largely captures the explanatory power of the trend variable (Table 6.54 and 6.55). Moreover, due to the multicollinearity between the *Trend*

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and *Number of EV Models* variables, it is suggested to drop one of the variables as otherwise the SEs might be inflated which can lead to a Type II error (Brooks, 2019).

Table 6.53: Regression Results:Trend Variable

Variable	Fixed Effects		First Differences	
	Marginal Effects	Robust Std. Err.	Marginal Effects	Robust Std. Err.
Environmental Awareness	0.010%	0.00950	-0.006%	0.01065
Chargers per 100km highway	-0.0943%***	0.00033	-0.1469%	0.00094
Fast Chargers per 100km highway	0.2169%***	0.00071	0.5337%	0.00422
Disposable Income	0.0094%	0.00013	0.0306%***	0.00009
Number EV Models	6.6788%***	0.02313	3.9819%	0.02579
LN(Electricity to Diesel Price)	-1.6264%**	0.72750	-2.0967%***	0.63630
Car Fleet	0.00%	0.00000	0.00%	0.00000
Subsidies	0.0108%***	0.00002	0.0072%***	0.00002
Trend	118.18%	339.83	5125.31%	402.812
Observations	193		163	
F-score	60.25***		53.63***	
Within R^2	0.7392			
Between R^2	0.3063			
Overall R^2	0.4974		0.4136	

Note: Country Fixed Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** p < 0.01

** p < 0.05

* p < 0.1

Table 6.54: Correlation with Trend Variable

	EA	Charging Points	Fast Chargers	Disposable Income	EV Models	$\ln \frac{Elec.}{Diesel}$	Car Fleet	Subsidies	Trend
EA	1.0000								
Chargers per 100km highway	-0.3641	1.0000							
Fast Chargers per 100km highway	0.3847	-0.5323	1.0000						
Disposable Income	-0.4577	0.5302	-0.2947	1.0000					
Number EV Models	0.4126	-0.1260	0.3222	-0.3082	1.0000				
$\ln \frac{Elec.}{Diesel}$	-0.5034	0.1888	-0.2363	0.2960	-0.4287	1.0000			
Car Fleet	-0.0463	0.2521	-0.1193	-0.3061	0.3548	-0.3112	1.0000		
Subsidies	0.2664	0.0057	0.0405	-0.2512	0.4083	-0.1288	0.3137	1.0000	
Trend	-0.3401	-0.1367	-0.1849	0.0779	-0.9412	0.3597	-0.4160	-0.4561	1.0000

Table 6.55: VIF Test Trend Variable

Variable	VIF	1/VIF
Trend	40.28	0.024827
Number EV Models	39.80	0.025126
Chargers per 100km highway	2.78	0.359520
Fast Chargers per 100km highway	2.35	0.424732
Disposable Income	1.67	0.600178
Environmental Awareness	1.62	0.617857
Car Fleet	1.57	0.637718
Electricity to Diesel Price	1.42	0.705678
Subsidies	1.30	0.769913

6.2.6.4 Random Effects Model

An RE model is executed to account for potential misspecifications of the baseline model. Although, the application of an RE model has not only been ruled out by the specification tests but also by looking at previous literature as well as the properties of the main independent variable, an RE model can further underscore the results of previous analyses. However, when running an RE model it must be kept in mind that it does not only consider the development of a determinant within a country over time, but also compares the values between the entities of the panel (Brooks, 2019). Consequently, this can lead to different significances of the included variables. For example, while the variable *Disposable Income* is not significant in the FE model, it is highly significant in the RE model. A potential explanation for this is that the average income of an household within a country does not strongly change over time. However, the average income of households between countries can strongly deviate, making this variable significant in the RE model. However, more importantly EA is neither in the FE nor the RE model a significant determinant of the EV market. Consequently, indifferent to potential misspecifications of the model, EA is an insignificant factor and therefore supports previous findings of this study.

Table 6.56: Regression Results: Random Effects Model

Variable	Random Effects		First Differences	
	Marginal Effects	Robust Std. Err.	Marginal Effects	Robust Std. Err.
Environmental Awareness	0.9163%	0.00768	-0.4871%	0.01007
Chargers per 100km highway	0.0272%	0.00066	-0.1229%	0.00090
Fast Chargers per 100km highway	0.1156%	0.00296	0.5549%	0.00434
Disposable Income	0.0167%***	0.00003	0.0323%***	0.00009
Number EV Models	6.2366%***	0.00463	6.4776%***	0.00933
LN(Electricity to Diesel Price)	-1.4068%**	0.65921	-2.1978%***	0.61671
Car Fleet	0.00%	0.00000	0.00%	0.00000
Subsidies	0.0101%***	0.00002	0.0077%***	0.00003
Observations	193		163	
Wald χ^2	872.23***		63.36***	
Within R^2	0.7291			
Between R^2	0.6787			
Overall R^2	0.7033		0.4093	

Note: Country Random Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** p < 0.01

** p < 0.05

* p < 0.1

6.2.6.5 Charging Infrastructure

Although, as discussed in Chapter 6.1.6.5, it is assumed that no endogeneity or multicollinearity problem arises from the inclusion of the charging infrastructure variable, is also checked for the robustness of the results when applying Google Trends as a surrogate for EA. In particular, three further regressions are carried out. In the first regression alternative both variables accounting for the charging infrastructure of a country are excluded. Furthermore, the second and third regression alternative exclude the CP and FC determinant, respectively, to check whether the significance of the coefficient of the of the main independent variable differs in comparison to the baseline regression. Looking at the results of the main independent variable reported in Table 6.57, it can be seen that EA remains an insignificant determinant in each regression alternative. Thus, this robustness test supports the results obtained from the main part of the investigation.

Table 6.57: Regression Results: Charging Infrastructure

Variable	w/o charger		w/o charger total		w/o charger fast	
	Marginal Effects	Robust Std. Err.	Marginal Effects	Robust Std. Err.	Marginal Effects	Robust Std. Err.
Environmental Awareness	0.8103%	0.00919	0.7971%	0.00920	0.9101%	0.00890
Chargers per 100km highway					-0.0552%	0.00040
Fast Chargers per 100km highway			-0.0670%	0.00076		
Disposable Income	0.0107%	0.00013	0.0106%	0.00013	0.0101%	0.00013
Number EV Models	6.7891%***	0.00664	6.8447%***	0.00689	7.1564%***	0.00783
LN(Electricity to Diesel Price)	-1.5124%**	0.68971	-1.5202%**	0.68854	-1.5979%**	0.70258
Car Fleet	0.00%	0.00000	0.00%	0.00000	0.00%	0.00000
Subsidies	0.0110%***	0.00002	0.0111%***	0.00002	0.0111%***	0.00002
Observations	193		193		193	
F-score	98.60***		83.11***		75.54***	
Within R^2	0.7355		0.7357		0.7381	
Between R^2	0.3404		0.3260		0.2996	
Overall R^2	0.5026		0.4933		0.4877	

Note: Country Fixed Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. Only Fixed Effects results are reported.

*** p < 0.01

** p < 0.05

* p < 0.1

6.3 Discussion of Results

Contradictory to the hypothesis, the results of this investigation exhibit no significant influence of the level of EA on the registration rate of new EVs. Based on the findings it cannot be ruled out that EA to some degree influences the EV market, however, the results suggest that other factors might have played a more important role. The outcome, when taking on a macro-economic perspective and

looking at actual sales data, does not confirm the findings of previous literature that predominantly investigated the determinants of EV purchase decisions at an individual level.

The TPB provides a possible explanation for these findings through the influence of the perceived behavioral control dimension. Perceived behavioral control, which can be understood as external factors that hinder the engagement in a certain behavior, is the only factor that has a direct influence on both intention and adoption behavior. Hence, it could be assumed that while EA has a significant positive impact on the intention to purchase an EV, the influence of factors such as high prices or limited charging infrastructure mitigates the positive influence of EA on actual EV adoption. Thus, hereby further support for the attitude-action gap in this research field is provided.

The results, however, correspond with the findings of de Rubens (2019) who carried out a comprehensive survey in five different Nordic regions with the objective of determining different customer groups and investigating customers' interest in purchasing EVs. After clustering the respondents into six different customer groups, the scholars found that although the group with the highest EA level has the largest interest in EVs, this group exhibits the second smallest ownership ratio of EVs. Even the customer group this study refers to as 'Sceptics' (a cluster of people that scored low on EA) demonstrates a more than four times higher EV ownership ratio. Subsequently, these findings support the analysis that EA does not significantly impact the sales ratio of EVs and that this can potentially be attributed to the fact that other variables have a stronger influence on the EV purchasing decisions in the investigated time period. For example, control variables shown to have a significant influence on the EV market in this study are the *Charging Points per 100km highway* and *Fast chargers per 100km highway*, the *Number of EV Models*, the electricity price in relation to the diesel price as well as *Subsidies*.

Based on these results and findings of previous literature, multiple hypotheses can be established that could explain the insignificant impact of EA on the EV market. Most of the hypotheses focus on potential barriers which need to be overcome before EA can develop into a decisive factor. First of all, EVs are a relatively new technology. To make this technology competitive to normal ICCs it requires a certain infrastructure. This infrastructure is mainly reflected in public charging points, which has been determined to be an important requirement (e.g. Sierzechula et al., 2014; Mersky et al., 2016). Thereby, not only the number of public charging

points is relevant but also the standardization of the charging process (Van Den Bossche et al., 2016; Hall and Lutsey, 2017). While the number of fast chargers has a significant positive impact on EV sales in our investigation, paradoxically, the total number of charging points exhibits a significant negative relationship to the EV ratio. This unexpected outcome is similar to that of Münzel et al. (2019) but will not be further discussed as it is not the focus of the present research.

Another barrier that hinders the expansion of the EV market is the high purchase prices of EVs compared to ICCs. Therefore, this type of car can, in the early stages, be seen to be primarily attractive to status seekers which usually have a high disposable income. As EV prices are assumed to continuously drop, it can be expected that this factor will become less relevant over time (de Rubens, 2019). Similarly to price, ICCs currently still have the advantage of a farther range than EVs which could further reduce the attractiveness of the latter.

A further hypothesis might be that very environmentally aware people might not yet see EVs as sustainable enough and therefore prefer other modes of transportation such as public transport. Concerns that have been expressed regarding the sustainability of EVs include the issue of non renewable energy sources used to power EVs, as well as the comparatively higher CO_2 emissions caused by the production, maintenance and disposal of EVs (Federal Ministry for the Environment Nature Conservation and Nuclear Safety, 2019). Similar to other factors, the advancement of technology in this sector is expected to reduce this issue.

It becomes clear that during the investigated time frame, customers faced several barriers that might have prevented them from purchasing EVs. As the market evolves, these barriers can be expected to become less significant compared to the barriers of purchasing an ICC. Therefore, we hypothesize that once the barriers have been reduced to a level where EVs become a feasible alternative to ICCs, EA will play a more significant role in the development of EV sales. Consequently, it is suggested to repeat this investigation at a later point in time. This recommendation can be further underscored when looking at the protests for EA (e.g. Fridays for Future) that took place in the last years. Studies have shown that demonstrations can significantly change people's awareness regarding a topic (Olteanu et al., 2015), wherefore people's EA potentially has significantly increased especially in the years 2018 and 2019 which are not included in this study.

As discussed in the introduction, EA is also an important topic for car manufacturers when advertising their products. However, based on our results it might be

favorable for car manufacturers to alter the focus and highlight other advantages of EVs to illustrate that some perceived barriers might have already been overcome. For example, several studies that have focused on total cost of ownership, found that the initial higher purchasing prices of EVs are to some extent compensated by lower operational costs (e.g. Wu et al., 2015; Lévy et al., 2017). Furthermore, the compensation effectiveness increases with the mileage of the car (Wu et al., 2015). Another potential characteristic to highlight in marketing, could be the technological features such as the acceleration of EVs to better attract the technological affine consumer group (de Rubens, 2019). Martin and Väistö (2016) for example found that Tesla which is seen to be one of the leading manufacturers of EVs primarily appeal to the hedonic motivation of consumers with their marketing strategy. This leads to another recommendation for future research. It is proposed to further investigate what kind of marketing messages are especially appealing to EV customers.

Another hypothesis recommended for investigation in future research involves the indirect influence of EA on the EV market via politics. This study supports prior findings that show, that subsidies have a significant influence on EV sales. A potentially interesting research question could be, whether EA has an influence on political decisions by increasing political actions such as subsidies or investments into sustainability research. Lastly, this study indicates, there are potentially significant differences in findings on a macroeconomic level as opposed to the individual consumer level. It is therefore recommended to conduct more research on a macroeconomic level to gain a better understanding of the actual effects on the market.

Like other studies, this study is of course not free of limitations. Although the methodology addresses several issues of other measurement approaches for EA, it also entails some drawbacks which are worth addressing. First of all, Twitter is at first sight limited by the users of this platform and thus does not represent the entire population. The users of this platform, however, are seemingly well diversified regarding their demographic characteristics. In addition, when comparing the demographics of the Twitter population and the individuals who are interested in purchasing EVs, according to previous literature, it can be seen that those characteristics correspond very closely. Similar to the population of Twitter users, the typical EV owners and potential customers of EVs tend to be younger, male, well educated and generally have above average income (Tien, 2018). Furthermore, as

discussed in the literature review, this social media platform potentially has a reach that exceeds its user base as it has been shown that Twitter activity influences media coverage.

Another limitation of this EA measure is that it solely relies on tweets written in the English language and only relies on two word pairs as search terms. This is the case because it was decided to use an existing database of tweet IDs due to the fact that older tweets could have been deleted and therefore might not be accessible anymore. This in turn could distort the results. For future research it could be beneficial to collect data in the native languages of the investigated countries as well, to get a more accurate measure of EA. It should however be noted that English is the most used language on Twitter and that Twitter's reach is not restricted by geographical barriers. Users therefore are able to follow and engage with users from various countries. For these reasons, and also because climate change is a global problem, it is assumed that the English tweets relatively closely capture EA also for non English speaking countries. In addition, as pointed out earlier, Twitter users are generally well educated and therefore it is likely that most users understand and speak English in addition to their native language. The results of the GT analysis further support this assumption as they led to the same results as the Twitter analysis despite covering search terms in local languages.

6.4 Conclusion

This study has investigated the impact of EA on the EV market. While previous studies in this field of research have focused on whether EA has a significant influence on an individual's purchase intention, this study takes on a macroeconomic perspective by examining the impact on actual EV registration rates. By applying a novel approach to measuring EA in this strand of literature in form of a Twitter keyword analysis, this study is able to contribute to existing research by gaining insights into the influence of EA at a macroeconomic level. Conducting a panel regression on 29 EU and EFTA countries, it was demonstrated, that contrary to what previous findings might suggest EA does not significantly influence the EV market. The results have been validated by the outcomes of different robustness tests. Moreover, another novel measurement of EA in form of a Google Trends analysis has been performed and yielded the same results. Based on the findings it cannot be ruled out that EA to some degree influences the EV market, however, the

results suggest that other factors might have played a more important role. In this study it is hypothesised that EA will become more relevant once the market has evolved and the factors that currently might still hinder EV purchasing decisions are minimised. Consequently, it could be of academic interest to repeat this study at a later point in time.

COUNTRY INNOVATIVENESS: AN ACCELERATOR OF THE ELECTRIC VEHICLE MARKET?

While in the previous chapter it has been uncovered that the altruistic factor EA has no significant influence on the EV market, in this chapter a focus will be laid on a more self centered determinant. In particular, it will be investigated whether a country's innovativeness level has an influence on the registration rate of EVs. The *Global Innovation Index* is employed as a surrogate of innovativeness that is capable of capturing the level of innovativeness for the three potential consumer groups of EVs, namely; the public, corporations and government. Thereby, this chapter contributes to the gap of literature that analyses the influence of this determinant on actual adoption behavior. More precisely, it is the first attempt to investigate the relationship between innovativeness and the EV market using market data. It can therefore be considered to be able to circumvent the biases of previous research focusing on this determinant. Moreover, by taking on a macroeconomic perspective, it is also able to shed light on how an innovative environment might foster the development of this important market.

To investigate the hypothesis established in Chapter 3.4.2.2, different statistical panel data regression models have been applied. The results provide support for the hypothesis, which means that a higher level of innovativeness leads to a faster adoption of EVs. Furthermore, evidence for a mediator function of innovativeness between wealth and EV adoption is also provided.

7.1 Descriptive Statistics

Initially the descriptive statistics will be analyzed to obtain a better understanding about the data being processed. Although, an analysis of some of the descriptive statistics has already taken place in relation to the first research question in the previous chapter, it is important to have another brief look at the values, as the investigated time period has changed. Furthermore, additional determinants will be introduced in this chapter, of which the descriptive statistics have not been analysed yet.

Table 7.1: Descriptive Statistics

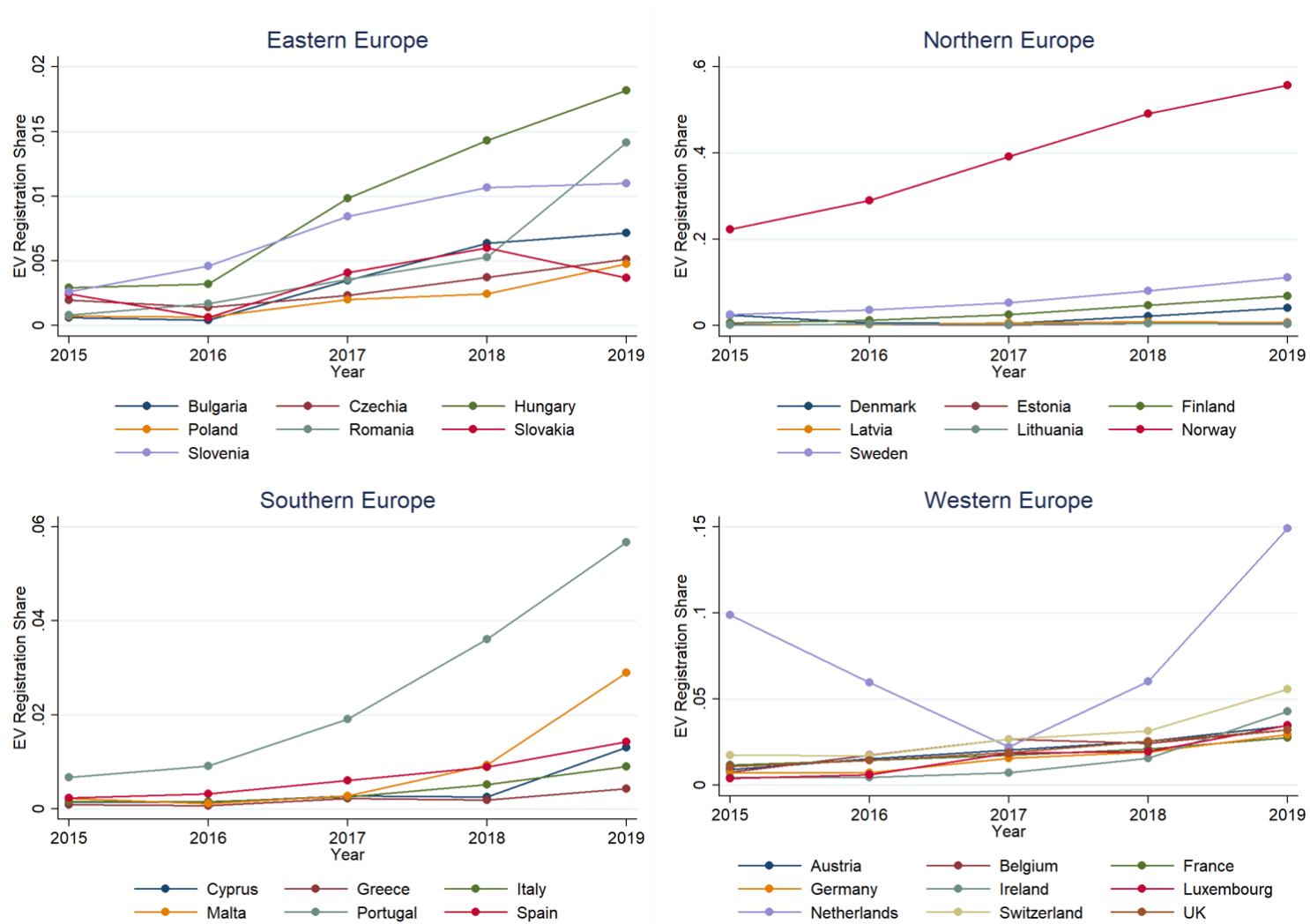
Variable		Mean	Std. Dev.	Min	Max	Observations
EV Registration Share	overall	0.0183502	0.0583824	0	0.5577991	N = 261
	between		0.0449579	0.0011702	0.2443921	n = 29
	within		0.0380721	-0.2115058	0.3317572	T = 9
Innovativeness	overall	50.54438	7.885153	34.18	68.4	N = 261
	between		7.851794	37.99444	66.81111	n = 29
	within		1.556251	45.47438	55.1208	T = 9
Disposable Income	overall	20091.38	5779.002	8678	33871.64	N = 261
	between		5714.507	10156.47	32118.63	n = 29
	within		1321.39	17082.72	24191.27	T = 9
Subsidies	overall	3429.224	3661.799	0	15123.85	N = 261
	between		3290.688	0	12843.95	n = 29
	within		1706.848	-2794.678	9330.414	T = 9
Charging Points Total	overall	2906.51	6857.928	0	50592	N = 261
	between		5032.793	16.22222	20748.67	n = 29
	within		4741.469	-16592.16	32749.84	T = 9
Fast Chargers	overall	278.4023	671.9427	0	5088	N = 261
	between		424.1447	0	1542.222	n = 29
	within		526.4443	-1263.82	3881.736	T = 9
Charging Points Total per 100km Highway	overall	144.5142	330.6184	0	2631.549	N = 261
	between		279.9259	1.020163	1424.007	n = 29
	within		182.65	-682.3606	1352.056	T = 9
Fast Chargers per 100km Highway	overall	18.88587	61.40311	0	655.0669	N = 261
	between		42.94373	0	219.9278	n = 29
	within		44.53001	-197.6002	454.025	T = 9
Electricity to Diesel Price	overall	0.0977933	0.0232329	0.0551923	0.1739604	N = 261
	between		0.0210411	0.0679812	0.1433685	n = 29
	within		0.0105196	0.0638049	0.1283852	T = 9
Trend	overall	7.608374	0.0012838	7.606388	7.610358	N = 261
	between		0	7.608374	7.608374	n = 29
	within		0.0012838	7.608374	7.610358	T = 9
Dwelling Type House	overall	58.29226	15.99105	33.1	95.6	N = 261
	between		16.18839	34.18889	93.18889	n = 29
	within		1.308881	54.60337	62.34782	T = 9
Income ratio 80 to 20	overall	4.838487	1.164892	3.03	8.32	N = 261
	between		1.138669	3.44444	7.196667	n = 29
	within		0.3167036	3.642931	6.139598	T = 9
Home Ownership rate	overall	74.12439	11.71042	41.3	96.8	N = 261
	between		11.83322	43.04444	96.21111	n = 29
	within		1.188733	70.04662	79.44662	T = 9

The analysis applied in this chapter covers a nine year time period from 2011 to 2019. While the time horizon has slightly changed compared to the investigation in

the previous chapter, the geographic focus with the 29 EU and EFTA states remains the same. When looking at the variables that are also considered in Chapter 6, it becomes evident that the extension of the time period has a strong influence on the descriptive statistics of the considered determinants. Specifically, the variables that represent the EV market as well as infrastructure are strongly affected. This is however, not surprising as markets that are in their early stages often experience exponential year on year growth (Jenn et al., 2013). To illustrate this behaviour and to provide general information about the development of the EV market in the years 2018 and 2019, a figure depicting the registration rate of EVs has been added to this chapter. As it can be seen in Figure 7.1, the registration rate of EVs has substantially increased in the additional two years, especially from 2018 to 2019. In the country Norway, EVs exhibited a registration share of 55.78% for all newly registered vehicles in the year 2019. Thus, it can be concluded that EVs have already replaced ICCs as the main vehicle type in this country.

The charging infrastructure of the EV market has also developed, when comparing the descriptive statistics of the previous chapter with the ones illustrated in Table 7.1. When just looking at the mean of the number of charging points per 100km highway, the number has increased by more than 40%.

Figure 7.1: EV Registration Rate 2015-2019



Focusing on the determinant Innovativeness, the descriptive statistics provide valuable insights about the main independent variable of this chapter. As discussed in the data description, a country's level of innovativeness is in this work represented by the Global Innovation Index. This index assigns scores to each country, depending on the level of the public's, government's and corporations' innovativeness, ranging from values of 0 to a maximum of 100. A mean value of 50.54 of the sample is therefore, exactly the middle of the range of possible scores. Considering the standard deviation, maximum and minimum values of the sample, it can be noticed that there is no strong deviation in most of the countries' innovativeness scores in the respective years. Moreover, the minimum and maximum values are relatively close to the sample mean and relatively far from the absolute possible minimum (0) or maximum (100). This is however not surprising as the study focus is laid on the EU and EFTA region, which consists of mostly developed countries.

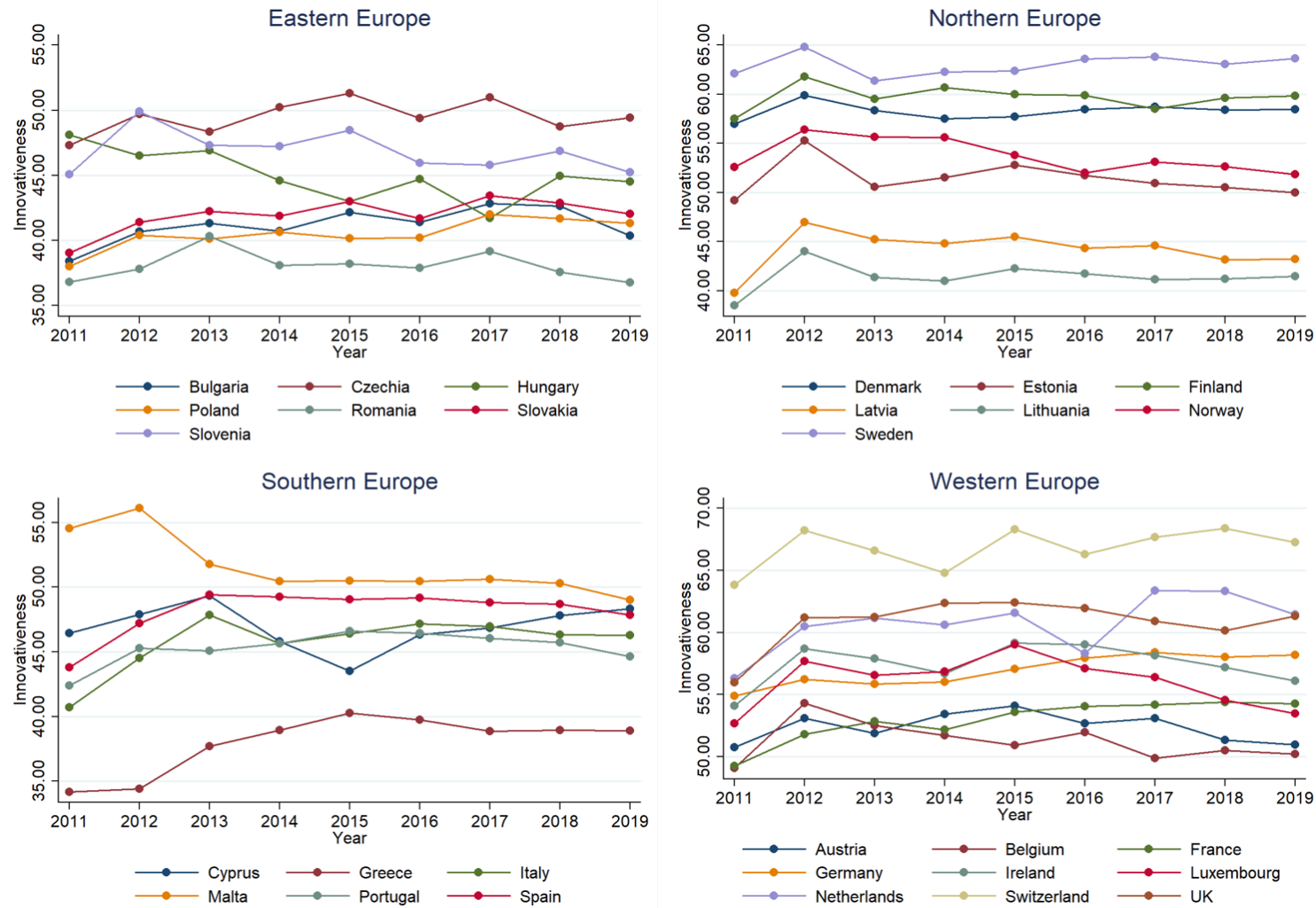
Another important observation that can be made from the descriptive statistics is that the variable innovativeness exhibits a small within variation. This means that a country's level of innovativeness changes only slowly over time. Literature often refers to such a determinant as a *sluggish* variable (e.g. Andreß et al., 2013; Bell and Jones, 2015). The lack of variation within a country becomes even more evident when comparing the between and within standard deviations of this variable. While the innovativeness level varies between countries with a standard deviation of about 7.85, a country's innovativeness level only varies with a standard deviation of about 1.56 within the investigated time period and is thus more than five times lower.

The inferences derived from the descriptive statistics can all be confirmed when looking at Figure 7.2, which depicts the development of the innovativeness level for each country. Although, the figure shows significant cross country differences, the innovativeness level within a country mostly remains at the same level. The reason for such a low within variation becomes clear when considering the characteristics of the variable. It is very unlikely that a country's innovativeness level severely changes, especially when looking at such a short time-period. Moreover, it is not uncommon that macroeconomic variables are slowly changing as they represent data of higher level entities and not individuals (Bell and Jones, 2015; Blaydes, 2006). In this particular case, the score of the country's innovativeness level index changes depending on the development of the average of the population's, government's and corporations' innovativeness. Thus, a multitude of individuals are

responsible for the development a country's innovativeness score assigned by this index, making fast developments fairly unlikely. Based on this analysis, it can already be concluded that a statistical approach that does not only consider within but also between variation is favourable for the investigation of this determinant.

The same observations apply to the three additional socio-economic/demographic variables *Dwelling Type House*, *Income ratio 80 to 20* and the *Home Ownership rate* that are added to this investigation. All of these variables exhibit a far greater between than within variation. It is now possible to consider these variables since the investigated time period could be extended by two years, which lead to an increase in the number of observations. Thus, the opportunity has arisen to include these determinants as additional potential explanatory variables as the possibility of over-identifying the model has diminished. Additionally, compared to the investigation of the previous study, a trend variable has replaced the number of EV models. This study had to resort to using a trend variable as no source providing reliable estimates for EV models was available for the years after 2017. The purpose of the trend variable is to capture the development of the available EV models as well as other factors such as decreasing battery prices. A detailed discussion of the descriptive statistics of the four variables mentioned at last will not take place, as they do not exhibit any peculiarities and are not the focus of this study.

Figure 7.2: Country Innovativeness Level



Before starting with the statistical analysis of the research question, it should be noted that throughout this chapter, instead of one model three different models are investigated. These models incorporate different specifications in regard to the included control variables and are as follows:

Table 7.2: Considered Variables in the Models

Variable	Model Variations		
	All Variables	Gen - Spec	w/o Chargers
Innovativeness	✓	✓	✓
Subsidies	✓	✓	✓
Charging Points Total	✓	✓	
Disposable Income	✓	✓	✓
Electricity to Diesel Price	✓	✓	✓
Trend	✓	✓	✓
Dwelling Type House	✓		✓
Home Ownership Rate	✓		✓
Income Ratio 80 to 20	✓		✓

In the first model the main independent and all control variables are included. To detect the model with the best data fit, a General-to-Specific (GTS) procedure is applied for the second model. The GTS implies that the model with the best data fit only includes the variables *Innovativeness*, *Disposable Income*, *Subsidies*, *Charging points per 100km highway* and the *Ratio of Electricity to Diesel price*. Lastly, following the approach of Münzel et al. (2019) a model omitting the charging infrastructure is defined. The reason for exclusion of this factor can be traced back to the problems discussed in Chapter 6.3, such as the unequal distribution of charging stations within a country.

7.2 Pooled OLS

Following the analysis of the descriptive statistics, a pooled OLS is initially executed to obtain first insights about the relationship between the main independent and dependent variable. The results of the pooled regression for all three models are depicted in Table 7.3. All regressions are performed with robust standard errors, accounting for the possibility of model misspecification. For each variable, the standard errors are also reported in brackets.

Table 7.3: Regression Results: Pooled OLS

	All variables	Gen - Spec	w/o Chargers
Innovativeness	7.6023%*** (0.01528)	6.0457%*** (0.01288)	8.6730%*** (0.01519)
Disposable Income	0.0089%*** (0.00002)	0.0069%*** (0.00002)	0.0124%*** (0.00002)
Subsidies	0.0094%*** (0.00002)	0.0077%*** (0.00002)	0.0115%*** (0.00002)
Chargers 100km highway	0.1098%*** (0.00020)	0.1244%*** (0.00021)	
LN(Electricity to Diesel Price)	-0.6902%** (0.28320)	-0.8465%*** (0.29668)	-0.8421%*** (0.28833)
Trend	1.32E+05%*** (44.6694)	1.53E+05%*** (44.5307)	2.32E+05%*** (44.8501)
Dwelling House	-0.7805%** (0.00388)		-0.8040%** (0.00385)
Income 80 to 20	0.8431% (0.04764)		-0.3575% (0.04898)
Home Ownership	2.0922%** (0.00794)		3.7638%*** (0.00934)
Observations	251	251	251
F-score	101.51***	130.40***	103.84***
R ²	0.7958	0.7894	0.7701

Note: The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** p < 0.01

** p < 0.05

* p < 0.1

The results of the first model suggest that except for the *Income 80 to 20* variable, each determinant is significant at least at a 5% significance level. Moreover, the variables *Innovativeness*, *Disposable Income*, *Subsidies*, *Chargers 100km highway* and the trend variable are significant at a 1% level. In addition to the *electricity to diesel price* variable, these are also the variables, the GTS procedure has identified to provide the best data fit. Consequently, the variables *Dwelling House* and *Home Ownership*, which have a significant influence on the EV market according to Model 7.1 should nevertheless be omitted based on the GTS approach. The explanation for this can be found in the higher F-score value. The R^2 of both models is with 0.7958 (Model All Variables) and 0.7894 (Model GTS) relatively high, suggesting a good data fit. The marginally higher explanatory power of the Model including all determinants can be explained with a larger number of control variables. The regression model excluding the charging infrastructure exhibits the lowest R^2 value of all three alternatives but a slightly higher F-score than the first model.

The signs and values of the coefficients of all variables in all models are as expected and not surprising. There is no change in the signs or large difference in the values of the coefficients between the models, which can be traced back to the omission of a variable. Furthermore, no variable that is significant in one model becomes insignificant in another model, and vice versa. Only the level of significance

of some determinants slightly changes between models. Most importantly, the main independent variable Innovativeness is highly significant at a 1% level and suggests a positive relationship between a country's level of innovativeness and the registration rate of EVs. A more thorough analysis of the results will however, not take place at this point as these results just provide a first idea on the influence of the drivers on the EV market. The structure of the data set suggests that regression models that are tailored to processing data in form of a panel are more suitable for the present data set. In the light of finding the most suitable regression model, several specification tests will be executed in the following chapter.

7.3 Model Specification

Different specification tests are executed in this chapter. While the first tests focus on detecting the specific panel data regression model, the other diagnostic statistics are performed to check whether the Gauss-Markov OLS assumptions are met.

7.3.1 Fixed Effects vs. Random Effects Model

Initially with the help of an F-test (Table 7.4) as well as a Breusch and Pagan (1979) LM test (Table 7.5) the poolability of the data is ruled out. A significant F-score as well as χ^2 value indicate that an FE and RE model are both favorable over the application of a pooled OLS regression.

Table 7.4: F-Test

	All variables	Gen - Spec	w/o Chargers
F	F(28, 213) = 7.14	F(28, 216) = 7.03	F(28, 214) = 8.49
Prob >F	0.0000	0.0000	0.0000

Table 7.5: Breusch and Pagan Lagrange Multiplier Test for Random Effects

	All variables		Gen. - Spec.		w/o Chargers	
	Var	sd = sqrt(VAR)	Var	sd = sqrt(VAR)	Var	sd = sqrt(VAR)
EV	3.188495	1.785636	3.188495	1.785636	3.188495	1.785636
e	0.3940381	0.6277245	0.4066812	0.6377156	0.4056716	0.6369236
u	0.2505369	0.5005366	0.2216115	0.4707563	0.4662756	0.6828438
	χ^2 (1)	73.99	χ^2 (1)	76.10	χ^2 (1)	188.28
	Prob > χ^2	0.0000	Prob > χ^2	0.0000	Prob > χ^2	0.0000

After ruling out the application of a pooled OLS, the question arises whether an FE or an RE model fits the data better and therefore provides more robust

estimates. For this purpose, following the recommendation of Wooldridge (2010) in case of heteroskedasticity in the error terms the Mundlak (1978) approach in form of an augmented regression is carried out.¹ The results of the auxiliary regressions depicted in Table 7.6 support the application of an FE model for the model variations including all variables and the GTS model. In contrast, for the model specification that omits the charging infrastructure, the use of an RE model is recommended.

Table 7.6: Mundlak Approach for FE vs. RE

	All variables	Gen - Spec	w/o Chargers
χ^2	$\chi^2 (8) = 224.86$	$\chi^2 (5) = 84.58$	$\chi^2 (7) = 10.54$
Prob > χ^2	0.0000	0.0000	0.1598

Although the Mundlak approach provides evidence in favour of an FE model, this study claims that an RE model provides more reliable results for the variable Innovativeness as it can better reflect the true population parameters. Therefore, it must first be understood what advantage an RE model provides in contrast to an FE model but also what additional downsides it entails. Considering the properties of the main independent variable as discussed in the descriptive statistics, an FE model might not be the best econometric approach to investigate the influence of a country's innovativeness level on the registration rate of EVs. As pointed out by several researchers, the ability of an FE model to control for time-invariant factors as well as factors that only differ between units which significantly helps to minimise the probability of omitted variable bias, becomes a major drawback when trying to analyse the influence of sluggish variables (e.g. Allison, 2009; Clark and Linzer, 2015; Bartels, 2008; Williams, 2018). Variables with little within variation will strongly correlate with the unit fixed effects dummy variables and will therefore most probably lead to insignificant results of such variables (Clark and Linzer, 2015). On the contrary, executing a random effects model despite the presence of unobserved heterogeneity can lead to omitted variable bias and therefore either inflate or deflate the regression coefficients. Thus, according to Allison (2009) and Williams (2018), there is often a trade-off between bias and the efficiency, in terms of smaller standard errors, of the coefficients when either applying an FE or RE model. In cases, when the RE model is however only slightly biased the application of such a model nevertheless the recommended as it provides estimates that are closer to the true population compared to those obtained by an

¹The results of a Hausman test for the three models can be found in Appendix B

FE model, since this approach is more efficient (Andreß et al., 2013). Moreover, Bell and Jones (2015) argue that FE models are too often applied as a default statistical approach neglecting the advantages of an RE model. The researchers criticise that with the application of an FE model, determinants are often being cut out of the investigation, although they might be of significant interest for researchers and practitioners. Therefore, they promote the application of an RE model, especially for studies focusing on higher-level entities, as not only information of within but also between variation can be utilised. Consequently, an RE model seems to be the preferred econometric approach when considering the scope of analysis, which is the investigation of a sluggish variable, in the present case. Nevertheless, in the following, if applicable, the diagnostic tests and final models will be executed and discussed for all alternatives with both RE and FE specification.

Determining an RE model as the most appropriate specification, econometric models can be defined for all three variations. As the variables are abbreviated in the regressions, Table 7.7 provides a definition for each variable used in the econometric models. In econometric terms, the first RE regression model can be defined as follows:

$$(7.1) \quad \begin{aligned} \ln(EV)_{it} = & \alpha_1 + \beta_1 I_{it} + \beta_2 DI_{it} + \beta_3 S_{it} + \beta_4 CP_{it} + \beta_5 \ln\left(\frac{EP}{DP}\right)_{it} \\ & + \beta_6 TR_{it} + \beta_7 DH_{it} + \beta_8 IN_{it} + \beta_9 HO_{it} + \epsilon_{it} \end{aligned}$$

The general econometric model for the GTS variant can be defined as:

$$(7.2) \quad \begin{aligned} \ln(EV)_{it} = & \alpha_1 + \beta_1 I_{it} + \beta_2 DI_{it} + \beta_3 S_{it} + \beta_4 CP_{it} + \beta_5 \ln\left(\frac{EP}{DP}\right)_{it} \\ & + \beta_6 TR_{it} + \epsilon_{it} \end{aligned}$$

Lastly, the third general econometric model which omits the charging infrastructure determinant can be defined as:

$$(7.3) \quad \begin{aligned} \ln(EV)_{it} = & \alpha_1 + \beta_1 I_{it} + \beta_2 DI_{it} + \beta_3 S_{it} + \beta_4 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_5 TR_{it} \\ & + \beta_6 DH_{it} + \beta_7 IN_{it} + \beta_8 HO_{it} + \epsilon_{it} \end{aligned}$$

where α_1 in each regression represents the “global” intercept term and the error term ϵ_{it} consists of an individual entity specific error term v_i which measures the

deviation of each entity's intercept from the global intercept and a general error term ε_{it} . All variables are defined in the table below.

Table 7.7: Variable Definition

Variable Abbreviation	Variable Name
<i>I</i>	Innovativeness
<i>DI</i>	Disposable Income
<i>S</i>	Subsidies
<i>CP</i>	Chargers 100km highway
$\ln(\frac{EP}{DP})$	LN(Electricity to Diesel Price)
<i>TR</i>	Trend
<i>DH</i>	Dwelling House
<i>IN</i>	Income 80 to 20
<i>HO</i>	Home Ownership

7.3.2 Gauss-Markov OLS Assumptions

In the following, four diagnostic tests will be executed respectively for the three models established in the previous section, to check whether the Gauss-Markov assumptions are met. These diagnostic tests entail a test for multicollinearity, misspecification, heteroskedasticity and autocorrelation for the models. Based on the results of the diagnostics it can be decided whether the models require additional specifications.

Starting to check for the presence of multicollinearity between the explanatory variables, a VIF test is executed. The results of the VIF tests as depicted in Table 7.8 indicate no significant multicollinearity between the explanatory variables in either of the models. The variable with the highest VIF score is *Disposable Income* for all three model alternatives. These scores are however, far below the threshold value of 10 and even below the conservative threshold of 5.

Table 7.8: VIF Test

Variable	All variables		Gen - Spec		w/o Chargers	
	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
Innovativeness	3.28	0.304775	2.37	0.422375	3.21	0.311725
Disposable Income	3.70	0.270491	2.82	0.354251	3.23	0.310072
Subsidies	1.76	0.569069	1.33	0.749236	1.68	0.594465
Chargers 100km highway	1.66	0.603737	1.42	0.704316		
LN(Electricity to Diesel Price)	1.37	0.732398	1.30	0.770179	1.35	0.739974
Trend	1.20	0.833459	1.15	0.868290	1.14	0.878159
Dwelling House	1.78	0.562236			1.78	0.562292
Income 80 to 20	1.54	0.650831			1.53	0.651842
Home Ownership	3.57	0.280295			3.12	0.320203
Mean VIF	2.20		1.73		2.13	

The second diagnostic that is executed is a Ramsey RESET test. A Ramsey RESET test is carried out to verify that the models are not misspecified. In this case

Ramsey RESET tests are carried out that include values of powers 2, 3 and 4 of the predicted dependent variable. When analysing the significance of the three models with the FE specification, only the model omitting the charging infrastructure seems to be misspecified. This result indicates that the charging infrastructure is, despite its controversy in previous literature, an important determinant to explain changes in the registration rate of EVs. In contrast to the models estimated with the FE specification, the Ramsey RESET results obtained from the models with the RE specification are all significant and therefore suggest to be misspecified. This outcome is however not surprising as previously discussed RE models almost always suffer from at least slight omitted variable bias (cf. Clark and Linzer, 2015).

Table 7.9: Ramsey RESET Test

	All variables		Gen - Spec		w/o Chargers	
	FE	RE	FE	RE	FE	RE
F-score	F(3, 28) = 1.47	$\chi^2(3) = 1172$	F(3, 28) = 1.17	$\chi^2(3) = 1088$	F(3, 28) = 13.37	$\chi^2(3) = 1545$
Prob >F	0.2449	0.0000	0.3375	0.0000	0.0000	0.0000

To test for homoskedasticity in the idiosyncratic errors, a visual analysis as well as diagnostic tests are applied. Plotting the residuals of the regression models against the fitted values, the graphs depicted in Figure 7.3 indicate the presence of heteroskedasticity. To verify this assumption Likelihood ratio tests for the three models are performed. The significant test statistics confirm that the idiosyncratic errors are indeed affected by heteroskedasticity.

Figure 7.3: Heteroskedasticity

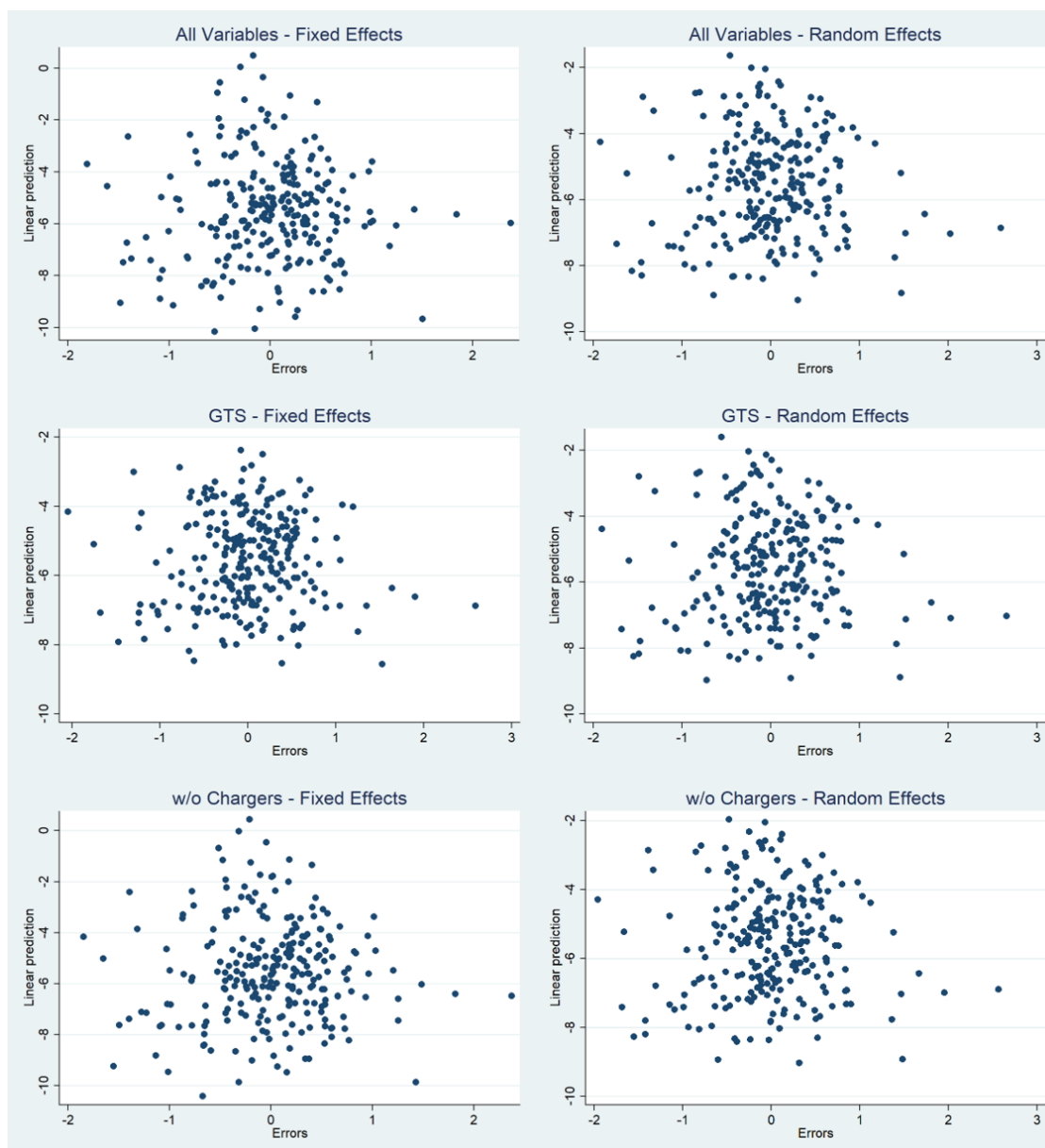


Table 7.10: Likelihood Ratio Test

	All variables	Gen - Spec	w/o Chargers
χ^2	$\chi^2(28) = 125.22$	$\chi^2(28) = 123.83$	$\chi^2(28) = 151.81$
Prob > $\bar{\chi}^2$	0.0000	0.0000	0.0000

The last diagnostic test that is carried out is a Wooldridge (2010) test for serial correlation. The results of this test shown in Table 7.11 provide evidence of serial correlation for all three models.

Table 7.11: Wooldridge Test for Autocorrelation

	All variables	Gen - Spec	w/o Chargers
F	F(1, 28) = 15.644	F(1, 28) = 18.013	F(1, 28) = 16.775
Prob >F	0.0005	0.0002	0.0003

Based on the results of the diagnostic tests, as in the previous chapter, robust SEs clustered on country level are applied to account for heteroskedasticity and serial correlation in the idiosyncratic errors. Furthermore, considering the Ramsey RESET test, it is assumed that the model including all variables and the GTS model provide more reliable results than the model omitting the charging infrastructure determinant, as they do not exhibit a significant test statistic for the FE specification. Lastly, although the auxiliary regression supports the application of an FE specification, the property of the main independent variable of being sluggish suggests that RE models are more suitable to investigate the research hypothesis and therefore provide more efficient results.

7.4 Panel Regression

As elaborated in the preceding subchapter, panel data regressions provide a better data fit than a pooled OLS. In the following, different panel data models will be applied. Thereby, the models proceed from basic FE and RE models to more advanced and specified mixed effects regression models. Moreover, the potential influence of *Innovativeness* as a moderator and mediator as hypothesised in Chapter 3.4.2.2 will be tested in this chapter. A comprehensive discussion that puts the results of all statistical models in conjunction takes place at the end of this chapter.

7.4.1 Random - and Fixed Effects Model

While, as previously discussed, it is expected that an RE model provides more efficient results in regard to the main independent variable, regressions for all three alternatives are also executed with an FE specification. The reason to also perform FE regressions is to spot and discuss potential differences in the outcomes. It should be noted that it is expected to obtain less valid results from the last model

as this regression omits the charging infrastructure of a country. According to the Ramsey RESET test performed in the previous chapter, omitting this variable results in a misspecification of this model. The results of the RE and FE regressions for the three models can be seen in Table 7.12.

First of all, when comparing the variables with the RE and FE specifications of the three models, important differences in the significances of some variables can be identified. While the main independent variable *Innovativeness* is significant at least at a 5% level for the models with the RE specification, it is only significant at a 10% level or even insignificant in the GTS case with an FE specification. Thus, the prevention of a potential bias due to omitted variables comes, as expected, with a high loss in efficiency. At this point, it is suggested that researchers have to weigh up the advantages with the disadvantages of the application of an RE model. Beck (2001) provides a potential guideline, researchers can orientate on. He claims that if the loss of explained variance is only slight, then it is better to suffer slight omitted-variable bias and apply an RE specification. Considering, the small increase in the within R^2 score when adding country fixed effects to the regressions, indicates no tremendous improvement in the explanatory power of the FE models. Consequently, according to Blaydes (2006) omitting country dummy variables in this case would only lead to negligible omitted variable bias. Thus, it is concluded that the gain of efficiency in estimating the coefficients of slowly changing variables, when applying an RE model, outweighs the disadvantage of a potential marginal omitted variable bias for these models in this research. Even though, it is argued in this analysis that an FE model specification is not suitable to analyse the established hypothesis, it nevertheless provides evidence for the significant influence of a country's level of innovativeness on the EV market. The coefficients are as expected positive and indicate that a one unit increase in a country's level of innovativeness will lead on average to a 6.40% (GTS model) or 7.80% (All variables model) increase in the registration rate of EVs. This means, using the results of the GTS model, assuming a country's EV registration rate was formally 1%, an increase in its innovativeness level would yield a registration rate of new EVs of 1,064% ($= 1\% * 6.40\%$).

The same observations that are made for the variable *Innovativeness*, apply to the variable *Disposable Income*. It is like *Innovativeness* a slowly changing variable in this regression model, wherefore a sole focus on the within variation yields no significant outcome for this determinant as shown in the results of the FE

specification. However, when also considering the variation between the countries, this factor exhibits significant coefficients at a 5% level for the first two models and at a 1% level for the model omitting the charging infrastructure. The coefficients of the variables are positive and indicate that if a significant relationship between these factors exists, a higher income would lead to more EV sales.

Another interesting difference, when comparing the RE and FE results appears in the coefficients of the determinant controlling for the charging infrastructure. While the coefficient obtained with an FE model specification is significant and negative, the coefficient of the model with an RE specification are insignificant and positive. Thus, considering the variation of the charging infrastructure between the countries in the model has not only an influence on the level of significance but also leads to a change in the sign of the coefficient. The inclusion of the between variation also has an impact on the significance of the ratio variable *Electricity to Diesel Price* by making it significant at a 1% level.

Determinants that do not strongly differ in regard to their level of significance based on the specification of the model are *Subsidies*, the trend variable, *Dwelling House*, *Income 80 to 20* or the *Home Ownership* ratio. While the former two variables are highly significant and exhibit a positive influence on the EV registration rate, the latter three are statistically not significant. This is another interesting observation as the variables *Dwelling House* and *Home Ownership* are significant in the pooled OLS regression.

As pointed out previously, there is often a trade-off between efficiency and bias of the estimators when applying either an FE or an RE model. Thus, neither the results that are obtained from the RE nor FE specification are perfect, as they might either be impacted by heterogeneity due to omitted variable bias or are unable to determine the actual impact of the main independent variable due to their inability to efficiently process sluggish variables (Bell and Jones, 2015). Therefore, the question arises whether a model exists that can provide a solution for this particular problem and cope with omitted variable bias as well as being able to determine valid estimates for sluggish variables. Two potential methodological solutions that can address this problem are discussed and applied in the subsequent subchapter.

Table 7.12: Regression Results: Random and Fixed Effects Models

Variable	All variables		Gen - Spec		w/o Chargers	
	RE	FE	RE	FE	RE	FE
Innovativeness	7.7950%*** (0.02922)	6.5198%* (0.03655)	6.4044%** (0.02704)	5.5761% (0.03818)	7.4826%** (0.03262)	7.1674%* (0.03782)
Disposable Income	0.0109%** (0.00005)	0.0080% (0.00011)	0.0083%** (0.00004)	0.0029% (0.00012)	0.0103%* (0.00006)	0.0082% (0.00011)
Subsidies	0.0105%*** (0.00002)	0.0111%*** (0.00003)	0.0099%*** (0.00002)	0.0101%*** (0.00002)	0.0104%*** (0.00002)	0.0103%*** (0.00002)
Chargers 100km highway	0.0088% (0.00021)	-0.0729%*** (0.00016)	0.0206% (0.00024)	-0.0540%*** (0.00018)		
LN(Electricity to Diesel Price)	-0.8437%* (0.50038)	-1.0236% (0.66677)	-0.9014%* (0.50400)	-0.7483% (0.59793)	-0.8599% (0.55365)	-0.9392% (0.65852)
Trend	2.5E+05%*** (70.6889)	4.0E+05%*** (116.867)	2.9E+05%*** (61.7457)	8.8E+05%*** (95.1317)	2.8E+05%*** (64.7173)	2.3E+05%*** (117.573)
Dwelling House	-0.5649% (0.00636)	-5.6851% (0.07167)			-0.4931% (0.00738)	-3.8301% (0.07138)
Income 80 to 20	4.7894% (0.08585)	23.5876% (0.15129)			7.3446% (0.10233)	14.8991% (0.16417)
Home Ownership	2.1209% (0.01988)	-6.0107% (0.04310)			1.3371% (0.02119)	-6.4267% (0.04482)
Observations	251	251	251	251	251	251
F/ χ^2 -score	850.49***	92.27***	547.25***	106.98***	767.35***	87.68***
Within R^2	0.7914	0.8078	0.7909	0.7988	0.7942	0.8012
Between R^2	0.7473	0.1339	0.7285	0.5010	0.7199	0.3457
Overall R^2	0.7697	0.3575	0.7620	0.6500	0.7587	0.5075

Note: Country Random and Fixed Effects models with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^\beta - 1)$. The Standard Errors are reported in brackets.

*** p < 0.01

** p < 0.05

* p < 0.1

7.4.2 Mixed Effects Models

The underlying idea of a mixed effects model is to merge the benefits of an FE and RE approach, by decomposing the within and between effects of a variable and thus allow it to consider the variation between the units but also make it robust to omitted variable bias. The foundation of a mixed effects model is an RE specification. In this RE model variables are included that represent the within variation of the time-varying determinants, thus reflecting the FE component in such a model. The mixed effects models considered in this investigation are the Hybrid model, also known as the within-between RE model (Bell et al., 2019), as well as the Correlated random-effects (CRE) model. As a reminder, one of the major differences between these two models is that while the component representing the cluster averages in the hybrid model estimates the between effect, the CRE model provides information about the difference of the within and between effects. Both models, however, include a component that represents the within effects of the considered time-varying determinants in the regression. More information about these approaches is provided in Chapter 5.2.4.

As most of the models are developed to explicitly process time-invariant variables, also known as level 2 variables, the determinant *Innovativeness* is as a second regression model alternative also transformed to a time-invariant variable. Therefore, the average of the *Innovativeness* score over the investigated time period is calculated for each country. It is hypothesised that due to the small variation of this variable, the average reflects the general innovativeness level of a country.

7.4.2.1 Hybrid Model

At first, the hybrid model is run as the results are easier to interpret and can be used for the interpretation of the results of the CRE model. A particular advantage of this model is that it does not only provide information about the estimates of an FE regression but also about the between cluster effects. Thus, this method is more or less a decomposition of the RE model, as the RE model is a weighted average of these particular effects (Schunck, 2013).

As discussed in the methodology section, the initial step in this approach is to decompose each time-varying variable into its between and within unit component. This is done following the Equation 5.36. The within unit component is obtained by deducting the observations of each country from its cluster average of the

investigated time-period and the between effect is calculated by employing the mean value for each country. These factors then replace the original time varying variables in the RE model. To better compare the outcomes of the regressions for the hybrid models with those of the corresponding RE and FE models, Table 7.13 reports the coefficients and their significances for all specifications. To distinguish the variables in the table, the variables representing the within unit deviation are assigned a *d* as a prefix and the ones representing the between effects obtained the prefix *m*. In this part only the results of the model incorporating all control variables are presented to avoid unnecessary repetition as the results of the other models are quite similar. The results for the other two model specifications can however be found in Appendix C.

As pointed out in the introduction of this subchapter, two hybrid models were performed which deviate from each other based on the property of the *Innovativeness* variable. While the first three columns reflect the regression results incorporating a time variant *Innovativeness* variable, this determinant is time-invariant in the last three columns. For both variations, there is no between effects estimate for the trend variable, as this variable only differs in time and not between countries.

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Table 7.13: Regression Results: Hybrid Models

Variable	Time variant Innovativeness			Time invariant Innovativeness		
	RE	FE	Hybrid	RE	FE	Hybrid
Innovativeness	7.7950%*** (0.02922)	6.5198%* (0.03655)		8.9723%*** (0.02652)	omitted	6.5949%*** (0.02324)
dInnovativeness			6.5198%* (0.03717)			
mInnovativeness			6.5949%*** (0.02329)			
Disposable Income	0.0109%** (0.00005)	0.0080% (0.00011)		0.0103%* (0.00005)	0.0056% (0.00012)	
dDisposable Income			0.0080% (0.00011)			0.0056% (0.00012)
mDisposable Income			0.0058%* (0.00003)			0.0058%* (0.00003)
Subsidies	0.0105%*** (0.00002)	0.0111%*** (0.00003)		0.0100%*** (0.00002)	0.0104%*** (0.00003)	
dSubsidies			0.0111%*** (0.00003)			0.0104%*** (0.00003)
mSubsidies			0.0060% (0.00004)			0.0060% (0.00004)
Chargers 100km highway	0.0088% (0.00021)	-0.0729%*** (0.00015)		0.0045% (0.00018)	-0.0778%*** (0.00018)	
dChargers 100km highway			-0.0729%*** (0.00016)			-0.0778%*** (0.00018)
mChargers 100km highway			0.2047%*** (0.00027)			0.2047%*** (0.00027)
LN(Electricity to Diesel Price)	-0.8437%* (0.50038)	-1.0236% (0.66677)		-0.7670% (0.49287)	-0.9021% (0.64692)	
dLN(Electricity to Diesel Price)			-1.0236% (0.67812)			-0.9021% (0.65789)
mLN(Electricity to Diesel Price)			-0.5939% (0.39015)			-0.5939% (0.38931)
Trend	2.5E+05%*** (70.6889)	4.0E+05%*** (116.867)		3.2E+5%*** (72.7266)	6.0E+5%*** (116.971)	
dTrend			4.0E+5%*** (118.857)			6.0E+5%*** (118.95)
mTrend			omitted			omitted
Additional Controls	✓	✓	✓	✓	✓	✓
Observations	251	251	251	251	251	251
F/ χ^2 -score	850.49***	92.27***	2580.65***	1318.60***	119.09***	2268.59***
Within R^2	0.7914	0.8078	0.8078	0.7871	0.8032	0.8032
Between R^2	0.7473	0.1339	0.8624	0.7436	0.0025	0.8624
Overall R^2	0.7697	0.3575	0.8333	0.7656	0.2409	0.8308

Note: Country Fixed and Random Effects models with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. In the time-invariant innovativeness regression models, the average of the innovativeness level for each country over the investigated time period is used. The determinants *DwellingTypeHouse* and *Income80to20ratio* and *HomeOwnership* are included in the regression but the results are not reported. Hybrid model is based on an RE specification.

*** p < 0.01

** p < 0.05

* p < 0.1

Starting with the interpretation of the results in the case where *Innovativeness* varies over time, it becomes evident that as expected, the within component of the hybrid model reflects an FE specification. The coefficients of the within estimators of the hybrid model are the same as in the FE specification and also exhibit significance scores at the same level. Moving on with the analysis and just focusing on

the hybrid model by comparing the estimates for the within and between effects, the results provide additional interesting insights. Looking at the main independent variable *Innovativeness* the estimate of the hybrid model indicates that the within-country effect of a unit increase in a country's level of innovativeness will lead to a 6.520% increase in the registration rate of new EVs. On the other side, the between component estimates the between-country effect of the innovativeness level (Schunck, 2013) and can be interpreted in the way a cross sectional regression would be interpreted (Andreß et al., 2013). The coefficient of the between country effect suggests that a country with a one unit higher innovativeness level exhibits a 6.595% higher registration rate of new EVs. Comparing the coefficients of the within and between effects estimator, it can be noticed that they do not strongly differ. A determinant that reveals an interesting difference of the within and between components in the hybrid model is the charging infrastructure. While, as in the FE specification, the coefficient of the within component is negative and therefore suggests that an improvement of the charging infrastructure leads to less registrations of EVs, the positive coefficient of the between component indicates that a country with a more advanced charging infrastructure exhibits a higher registration rate of EVs. The other variables do not show any particular specialties and can be interpreted in the same manner as the variables *Innovativeness* and *Chargers per 100km highway*.

Focusing now on the case where country innovativeness is modelled as a time-invariant determinant, no decomposition in terms of within- and between effects is made for this particular variable in the hybrid model. This is because this variable now incorporates the properties of a level 2 determinant and thus has no variation within a cluster (country). This also caused the omission of this determinant in the FE model specification. Consequently, as for all level 2 variables, the estimation of this variable solely relies on the differences between the countries. Since the time-invariant *Innovativeness* variable was calculated based on the within cluster average, it is not surprising that the coefficient in this model is the same as the coefficient for the between estimate in the first hybrid model. Moreover, as the cluster averages of all time-varying variables have not changed, the results of the between component estimates do not differ from the ones obtained from the first hybrid model. Furthermore, it can be seen that also in this model the estimates of the within-components match those of the FE model.

Returning now to the differences of the coefficient estimates of the within

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and between component, a hybrid model provides the great advantage that each variable can be tested individually for equivalence of the component estimates. Thus, it is more flexible than a Hausman (1978) specification test (Andreß et al., 2013), that tests whether the within and between effects of the entire model differ, and makes it redundant (Bell and Jones, 2015). The equivalence of the between and within effects are tested by performing an augmented regression test for each variable (Mundlak, 1978; Jones et al., 2007; Schunck, 2013) and the test results are presented in Table 7.14. Carrying out an augmented regression, the results can be interpreted in the way that an insignificant Wald χ^2 -score suggests that the within and between effects do not significantly differ and an RE specification for this variable can be used.

Table 7.14: Wald Test for Equivalence of Within and Between Estimates

Tested variables	χ^2 (1)	Prob > χ^2	RE is appropriate?
<i>Time variant Innovativeness</i>			
dInnovativeness - mInnovativeness = 0	0.00	0.9837	✓
dDisposable Income - mDisposable Income = 0	0.04	0.8452	✓
dSubsidies - mSubsidies = 0	0.89	0.3467	✓
dChargers 100km highway - mChargers 100km highway = 0	86.23	0.0000	X
dLN(Electricity to Diesel Price) - mLN(Electricity to Diesel Price) = 0	0.52	0.4723	✓
dTrend - mTrend = 0	48.78	0.0000	X
<i>Time invariant Innovativeness</i>			
dDisposable Income - mDisposable Income = 0	0.00	0.9831	✓
dSubsidies - mSubsidies = 0	0.73	0.3942	✓
dChargers 100km highway - mChargers 100km highways = 0	78.85	0.0000	X
dLN(Electricity to Diesel Price) - mLN(Electricity to Diesel Price) = 0	0.27	0.6048	✓
dTrend - mTrend = 0	53.53	0.0000	X

Note: The tests are post diagnostic tests for the Hybrid models depicted in Table 7.13.

Analysing the test results of the augmented regression, except the charging infrastructure determinant and the trend variable, all determinants exhibit an insignificant Wald χ^2 -score for both model alternatives, *Innovativeness* as a time-variant and time-invariant variable. Consequently, the null hypothesis of equality of the coefficients obtained from the within and between estimates is failed to be rejected for the majority of the determinants. This provides evidence for the assumption made in Chapters 7.3.1 and 7.4.1, that an RE specification, which calculates a weighted average of the between and within effects of a variable, does not over- or underestimate the effects of these variables. Thus, as the within and between estimates are almost the same, it is suggested to model these variables with an RE specification (Schunck, 2013).

The cause for the significant result of the Wald χ^2 -score for the charging infrastructure is different to the one for the trend variable. The explanation for the

significant test result for the trend variable is quite straight forward. Since this variable only differs in time but not between the countries, there is no between effect that could be determined. Thus, there is obviously a difference between the coefficient of a within effect and a non existing between effect. The explanation for differing within and between effects of the charging infrastructure determinant is however slightly more complicated. As already spotted, while the coefficient of the within estimator is negative, the coefficient of the between estimator exhibits a positive sign and is relatively high. On the one hand, this allows the conclusion that the charging infrastructure correlates with other country specific factors, which are currently not considered in the regression model. This would lead to an overestimation of the charging infrastructure determinant in an RE model specification and advises to employ an FE specification for this determinant (Schunck, 2013). On the other hand, the between effects estimate shows the expected and intuitively assumed positive relationship between the charging infrastructure and the registration rate of EVs. The problem with this determinant is however, as discussed in the previous chapter, that there are still severe issues with the charging infrastructure as for example EVs provide the possibility to be recharged at home, charging stations are unevenly distributed throughout the country or the lack of standardization of the charging stations (Hall and Lutsey, 2017; Münzel et al., 2019). Determining the specific cause is however beyond the scope of this investigation and will not help to answer the research hypothesis. Moreover, it is unlikely to detect the specific omitted variable that causes this bias. As argued by Clarke (2005), the random inclusion of determinants does also not provide additional advantages and will unlikely decrease the likelihood of omitted variable bias when the true specification is unknown. Thus, in this case the most appropriate way to model the charging infrastructure and trend variable is to keep them decomposed in their within and between effects.

Based on the results of the augmented regression, two different variations of the hybrid model for each case, *Innovativeness* as a time-variant and time-invariant variable are established. The first version will collapse the within and between decomposition of the variables, that do not exhibit a significant Wald χ^2 test into their original form. Therefore, these variables will be treated with an RE specification in the regression. The results of the regressions with this specification can be seen in columns 1 and 3 in Table 7.15. Columns 2 and 4 of Table 7.15 present the regression results of the second variation of the hybrid model. In this

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alternative, only the *Innovativeness* variable will be transformed into its original condition and therefore obtains an RE specification.

Table 7.15: Regression Results: Final Hybrid Models

Variable	Time variant Innovativeness		Time invariant Innovativeness	
	Hybrid Final	Hybrid Final Only Inno. RE	Hybrid Final	Hybrid Final Only Inno. RE
Innovativeness	5.6905%** (0.02830)	6.5707%*** (0.02351)	5.9342%** (0.02578)	6.5949%*** (0.02324)
dInnovativeness				
mInnovativeness				
Disposable Income	0.0048% (0.00004)		0.0045% (0.00004)	
dDisposable Income		0.0080% (0.00012)		0.0056% (0.00012)
mDisposable Income		0.0059%* (0.00003)		0.0058%* (0.00003)
Subsidies	0.0091%*** (0.00002)		0.0087%*** (0.00002)	
dSubsidies		0.0111%*** (0.00003)		0.0104%*** (0.00003)
mSubsidies		0.0059% (0.00004)		0.0060% (0.00004)
Chargers 100km highway				
dChargers 100km highway	-0.0586%*** (0.00017)	-0.0729%*** (0.00016)	-0.0632%*** (0.00015)	-0.0778%*** (0.00018)
mChargers 100km highway	0.2149%*** (0.00020)	0.2048%*** (0.00026)	0.2170%*** (0.00024)	0.2047%*** (0.00027)
LN(Electricity to Diesel Price)	-0.7435% (0.50609)		-0.6872% (0.49725)	
dLN(Electricity to Diesel Price)		-1.0245% (0.65889)		-0.9021% (0.65789)
mLN(Electricity to Diesel Price)		-0.5943% (0.38921)		-0.5939% (0.38931)
Trend				
dTrend	7.4E+5%*** (57.686)	4.0E+5%*** (117.38)	8.8E+5%*** (59.493)	6.0E+5%*** (118.95)
mTrend	omitted	omitted	omitted	omitted
Additional Controls?	✓	✓	✓	✓
Observations	251	251	251	251
F-score	1731.33***	2597.55***	1968.93***	2268.59***
Within R^2	0.8021	0.8078	0.7982	0.8032
Between R^2	0.8497	0.8624	0.8519	0.8624
Overall R^2	0.8247	0.8333	0.8236	0.8308

Note: The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. In the time-invariant innovativeness regression models, the average of the innovativeness level for each country over the investigated time period is used. The determinants *DwellingTypeHouse* and *Income80to20ratio* and *HomeOwnership* are included in the regression but the results are not reported. Hybrid model is based on an RE specification.

*** p < 0.01

** p < 0.05

* p < 0.1

The results reveal, that the variables *Innovativeness*, *Subsidies*, *Chargers 100km Highway* and the trend variable are significant for the models incorporating the first variation of the hybrid model. Interestingly, compared to the standard RE

model (see Table 7.12), the determinant *Disposable Income*, which was previously significant at a 5% level, although modeled with an RE specification in this hybrid model, exhibits no significant influence on the EV market. In general, except for the trend variable, the coefficients of the hybrid model are slightly smaller in absolute terms compared to the ones of the original RE model. A potential explanation for this could be that the estimator of the charging infrastructure and the trend variable were wrongly estimated in the RE model due to omitted variable bias which could have impacted the estimates of the other variables. Nevertheless, the deviations of the coefficients are relatively small when considering the properties of the variables and putting them into relation with the second variation of the hybrid model.

The second variation of the hybrid model was performed to investigate the influence of the main independent variable on the EV market with the sources of noise, in terms of omitted variable bias, reduced to a possible minimum. Therefore, only the innovativeness variable was modeled with an RE specification. In the case where innovativeness is time-invariant the results are the same as those obtained from the original hybrid model. This is not surprising, as these models are the same. Since innovativeness is a level 2 variable in this case and therefore exhibits no within effects, the only way to incorporate this determinant in the hybrid model is in its original form. Consequently, since only *Innovativeness* is supposed to be included with an RE specification in this model and no other time-variant determinant, the same model as the original hybrid model is obtained. When looking at the results of the hybrid model regression where *Innovativeness* varies over time and is the only variable modeled with an RE specification, the obtained coefficient is significant at a 1% level. Moreover, the coefficient value is 6.57% and therefore close to the between- and within estimates obtained in the original hybrid model as well as the coefficient of the FE model, which is statistically considered to be the most unbiased. Considering, that the RE model estimate is a weighted average of the between effects and within effects estimates and the model has not changed in a different aspect, this results is however not surprising. The coefficients of the between and within effects of the other variables exhibit no difference to the original hybrid model in regard to their value or significance level.

It can be concluded that the coefficients of the original RE model might be a little bit biased. However, considering the properties and scale of the variables, the coefficients of the variables of the RE model do not strongly deviate from those

obtained from the hybrid models. The model that provides estimates for the main independent variable of this investigation that are the closest to the FE estimates, are those from the hybrid model that only includes the variable *Innovativeness* with an RE specification in the regression. Since the estimates that are obtained due to an FE approach are considered to be the least biased by practitioners, it can be concluded that this hybrid model provides the best estimates by simultaneously benefitting from the more efficient RE estimation approach. In this case most of the effects are similar to those of the original hybrid model and the variable can be expected to be not strongly affected by omitted variable bias as the estimate represents a weighted average of the within and between effects, which coefficients were proven to not significantly differ.

As presented in this section, the hybrid model provides a great environment to more flexibly execute test procedures than an FE or RE model would allow. As a consequence, Andreß et al. (2013) even recommends that a hybrid model should be the panel data regression model to begin with. Another mixed effects model that can be applied is the CRE model. Although several scholars advise to employ the hybrid model instead of the CRE model, as it provides more additional information (Schunck, 2013), the CRE model is nevertheless performed in the following section. Since this procedure does not provide significant new information, it should rather be considered as a robustness test for the hybrid model.

7.4.2.2 Correlated Random Effects Model

A different mixed effects model that has received widespread attention in academia is the CRE model. In contrast to the hybrid model, when applying a CRE model, in this case, the estimates obtained for the cluster means do not reflect the between differences of the countries but estimate the difference between the within and between effects. Thus, the application of a CRE model provides information about the extent to which unobserved heterogeneity affects the between estimates of the previously established hybrid model (Schunck, 2013). Theoretically, the results of the within component of the CRE model should be the same compared to the demeaned within effects of the hybrid and the estimates of the FE model. This is however, not the case when including the trend variable in its original form into the regression as it can be seen when comparing the results of Table D.1 in the Appendix with those of Table 7.13. A potential explanation for the divergence of the coefficients is the inclusion of a variable that does not differ between countries.

When including the trend variable, no cluster mean of this determinant is considered that can account for between-cluster differences in the variables. Therefore, the demeaned form of the trend variable is used in this part to account for this peculiarity and to ensure that the within estimates of the three different model specifications are the same.

Table 7.16: Regression Results: Correlated Random Effects Models

Variable	Time variant Innovativeness			Time invariant Innovativeness		
	RE	FE	CRE	RE	FE	CRE
Innovativeness	7.7950%*** (0.02922)	6.5198%* (0.03655)	6.5198%* (0.03717)	8.9723%*** (0.02652)	omitted	6.5989%*** (0.02327)
mInnovativeness			0.0744% (0.03445)			
Disposable Income	0.0109%** (0.00005)	0.0080% (0.00011)	0.0080% (0.00011)	0.0103%* (0.00005)	0.0056% (0.00012)	0.0056% (0.00012)
mDisposable Income			-0.0021% (0.00011)			0.0003% (0.00011)
Subsidies	0.0105%*** (0.00002)	0.0111%*** (0.00003)	0.0111%*** (0.00003)	0.0100%*** (0.00002)	0.0104%*** (0.00003)	0.0104%*** (0.00003)
mSubsidies			-0.0052% (0.00005)			-0.0045% (0.00005)
Chargers 100km highway	0.0088% (0.00021)	-0.0729%*** (0.00015)	-0.0729%*** (0.00016)	0.0045% (0.00018)	-0.0778%*** (0.00018)	-0.0778%*** (0.00018)
mChargers 100km highway			0.2776%*** (0.00030)			0.2825%*** (0.00032)
LN(Electricity to Diesel Price)	-0.8437%* (0.50038)	-1.0236% (0.66677)	-1.0236% (0.67812)	-0.7670% (0.49287)	-0.9021% (0.64692)	-0.9021% (0.65789)
mLN(Electricity to Diesel Price)			0.4326% (0.60472)			0.3094% (0.60178)
dTrend	2.5E+05%*** (70.6889)	4.0E+05%*** (116.867)	4.0E+5%*** (118.857)	3.2E+5%*** (72.7266)	6.0E+5%*** (116.971)	6.0E+5%*** (118.955)
mTrend			omitted			omitted
Observations	251	251	251	251	251	251
F-score/ χ^2	850.49***	92.27***	2546.99***	1318.60***	119.09***	2242.46***
Within R^2	0.7914	0.8078	0.8078	0.7871	0.8032	0.8032
Between R^2	0.7473	0.1339	0.8624	0.7436	0.0025	0.8624
Overall R^2	0.7697	0.3575	0.8333	0.7656	0.2409	0.8308

Note: Country Fixed Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. In the time-invariant innovativeness regression models, the average of the innovativeness level for each country over the investigated time period is used. The determinants *DwellingTypeHouse* and *Income80to20ratio* and *HomeOwnership* are included in the regression but the results are not reported. CRE model is based on an RE specification.

*** p < 0.01

** p < 0.05

* p < 0.1

The results in Table 7.16 show that as expected the within estimates of the CRE model exhibit the same values as the FE and hybrid model. Thus, demeaning the trend variable has the aspired effect on the coefficients. Comparing the factors in the regressions of the CRE model that are supposed to estimate the difference of the between and within effects, they all show with negligible discrepancies the anticipated values for the coefficients. In particular, it can be seen that:

$$m\beta_H - d\beta_H = m\beta_{CRE}$$

where β represents the parameters of the determinants of the regression models and the subscripts H and CRE stand for the hybrid and CRE model, respectively. Employing the main independent variable *Innovativeness* (time-varying case) of this investigation as an example, it can be seen that the estimated effect of the CRE model is with a value of 0.0744% almost equal to the calculated difference of 0.0751% (6.5949% - 6.5198%) of the within and between effects of the hybrid model. The values 0.0744% or 0.0751%, respectively, therefore indicate that the within and between estimates for the determinant *Innovativeness* differ by approximately these amounts.

To check whether these are significant differences in the estimates, it makes sense to initially look at the significances of the within and between estimate differences. Focusing on the significances of the coefficients reported in Table 7.16 the results support the findings obtained in the previous subchapter. The only determinant, that accounts for the difference of the between and within effects, that exhibits a significant influence on the EV market is *Chargers 100km highway*. This finding is a first indication that there is a significant difference between the within and between effect and is therefore in line with the previous analysis. To formally test the assumption that the within and between estimate are significantly different, an augmented regression as in the hybrid model can be executed (Schunck, 2013). Since the cluster mean component in a CRE model already represents the difference of the between and within estimate, it only has to be tested whether this coefficient is significantly different to 0.

Table 7.17: Wald Test for Equivalence of Within and Between Estimates CRE Models

Tested variables	χ^2 (1)	Prob > χ^2	RE is appropriate?
<i>Time variant Innovativeness</i>			
mInnovativeness = 0	0.00	0.9828	✓
mDisposable Income = 0	0.04	0.8472	✓
mSubsidies = 0	0.91	0.3404	✓
mChargers 100km highway = 0	86.10	0.0000	X
mLN(Electricity to Diesel Price) = 0	0.51	0.4753	✓
mTrend = 0	n.a.	n.a.	n.a.
<i>Time invariant Innovativeness</i>			
mDisposable Income = 0	0.00	0.9812	✓
mSubsidies = 0	0.73	0.3875	✓
mChargers 100km highway = 0	78.68	0.0000	X
mLN(Electricity to Diesel Price) = 0	0.26	0.6077	✓
mTrend = 0	n.a.	n.a.	n.a.

Note: The tests are post diagnostic tests for the CRE models depicted in Table 7.16.

Unsurprisingly, the results of the augmented regression confirm the findings of the previous subchapter and only reject the null hypothesis that the difference of the within and between estimates is equal to 0 for the charging infrastructure determinant. Thus, they provide evidence for an RE specification for all variables except *Charger 100km highway*. Consequently, the same approach as in the previous chapter is followed and two additional CRE regressions for each alternative, *Innovativeness* as a time-variant and time invariant variable, are executed. The model specifications again distinguish themselves from each other in the way, that while in the first alternative all determinants that did not exhibit a significant Wald χ^2 obtained an RE specification, in the second alternative only the variable *Innovativeness* is modeled with an RE specification.

Table 7.18: Regression Results: Final Correlated Random Effects Models

Variable	Time variant Innovativeness		Time invariant Innovativeness	
	CRE Final	CRE Final Only Inno. RE	CRE Final	CRE Final Only Inno. RE
Innovativeness	5.6961%** (0.02820)	6.5629%** (0.02509)	5.9438%** (0.02570)	6.5989%*** (0.02327)
mInnovativeness				
Disposable Income	0.0049% (0.00004)	0.0080% (0.00012)	0.0045% (0.00004)	0.0056% (0.00012)
mDisposable Income		-0.0021% (0.00011)		0.0003% (0.00011)
Subsidies	0.0091%*** (0.00002)	0.0111%*** (0.00003)	0.0087%*** (0.00002)	0.0104%*** (0.00003)
mSubsidies		-0.0051% (0.00005)		-0.0045% (0.00005)
Chargers 100km highway	-0.0585%*** (0.00017)	-0.0729%*** (0.00016)	-0.0632%*** (0.00015)	-0.0778%*** (0.00018)
mChargers 100km highway	0.2733%*** (0.00025)	0.2777%*** (0.00029)	0.2800%*** (0.00025)	0.2825%*** (0.00032)
LN(Electricity to Diesel Price)	-0.7417% (0.50443)	-1.0244% (0.66209)	-0.6857% (0.49561)	-0.9021% (0.65789)
mLN(Electricity to Diesel Price)		0.4328% (0.59771)		0.3094% (0.60178)
dTrend	7.4E+5%*** (57.707)	4.0E+5%*** (117.45)	8.8E+5%*** (59.504)	6.0E+5%*** (118.955)
mTrend	omitted	omitted	omitted	omitted
Additional Controls?	✓	✓	✓	✓
Observations	251	251	251	251
F-score	1721.51***	2464.65***	1951.54***	2242.46***
Within R^2	0.8021	0.8078	0.7982	0.8032
Between R^2	0.8500	0.8624	0.8522	0.8624
Overall R^2	0.8248	0.8333	0.8237	0.8308

Note: The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. In the time-invariant innovativeness regression models, the average of the innovativeness level for each country over the investigated time period is used. The determinants *DwellingTypeHouse* and *Income80to20ratio* and *HomeOwnership* are included in the regression but the results are not reported. CRE model is based on an RE specification.

*** p < 0.01

** p < 0.05

* p < 0.1

When looking at the results of the final CRE models in Table 7.18, it can be noticed that they barely deviate from those obtained from the final hybrid models. Thus, a repetition of the interpretation of the results does not take place and it is rather referred to read the concluding remarks of the previous subchapter. Nevertheless, what should be emphasised at this stage is, that although the estimates obtained from the RE model are relatively close to those of the mixed effects models, the mixed effects estimates should be favoured as they better control for the between-cluster differences of the time-varying determinants. Moreover, considering the research hypothesis of this investigation, in this study it is expected that the most appropriate estimates are obtained from the models that solely include the *Innovativeness* variable with an RE specification. This conclusion is made based on the fact that, on the one hand, when including the cluster mean of the time varying control variables, it corrects for between cluster differences in this variable, thus limiting the probability of potential biases (Schunck, 2013). On the other hand, it ensures that the variable is estimated with the most efficient approach in form of an RE specification.

7.4.3 Innovativeness as a Moderator

With this chapter an attempt is made to respond to the call of Al-Jundi et al. (2019) to analyse whether income has a moderating influence on EV adoption of innovative consumers. However, as argued in the literature review, this research hypothesises that the moderating role between innovativeness and wealth is reversed and that rather innovativeness exercises a moderating influence on the relationship between wealth and EV adoption. This assumption is based on the fact that EVs are more expensive than comparable ICCs, especially in the early years after market introduction. Thus, a certain level of wealth is considered to be a requirement to be able to even afford an EV. People might exhibit a high level of innovativeness but are unable to purchase an EV because they are not wealthy enough.

Although, the decision which variable plays a moderating role is important from a theoretical point of view, it is irrelevant from an econometric perspective and has no influence on the statistical approach that is applied. The variables reflecting wealth and innovativeness are combined in an interaction term, which in this case is termed $Inno. * DI$, and therefore does not require a specification about the direction of the variables influence. The moderation effect of country innovativeness is tested with the three initial regression alternatives; all variables included, the GTS model and only excluding the charging infrastructure. Furthermore, the moderation effect of Innovativeness is tested for in two hybrid models. While the first hybrid model regresses the interaction term with a model specification that distinguishes between within- and between effects, RE specifications are applied to the variables of the second model for which an augmented regression does not exhibit significant results.

CHAPTER 7. COUNTRY INNOVATIVENESS: AN ACCELERATOR OF THE ELECTRIC VEHICLE MARKET?

Table 7.19: Regression Results: Innovativeness as Moderator

Variable	Baseline Regressions			Hybrid Models	
	All Variables	Gen-Spec	w/o Chargers	Hybrid	Hybrid Final
Innovativeness	14.0077% (0.08831)	12.1216% (0.07814)	13.1873% (0.09805)		11.3044% (0.08384)
dInnovativeness				10.7189% (0.13345)	
mInnovativeness				16.5486%*** (0.05323)	
Disposable Income	0.0245% (0.00015)	0.0211% (0.00013)	0.0228% (0.00016)		0.0175% (0.00014)
dDisposable Income				0.0175% (0.00026)	
mDisposable Income				0.0280%* (0.00014)	
Inno.*DI	-0.0003% (0.00000)	-0.0003% (0.00000)	-0.0002% (0.00000)		-0.0002% (0.00000)
dInno.*DI				-0.0002% (0.00001)	
mInno.*DI				-0.0004%* (0.00000)	
Subsidies	0.0100%*** (0.00002)	0.0093%*** (0.00002)	0.0101%*** (0.00002)		0.0087%*** (0.00002)
dSubsidies				0.0109%*** (0.00003)	
mSubsidies				0.0041% (0.00004)	
Chargers 100km highway	0.0135% (0.00019)	0.0239% (0.00023)			
dChargers 100km highway				-0.0703%*** (0.00014)	-0.0547%*** (0.00015)
mChargers 100km highway				0.2105%*** (0.00025)	0.2165%*** (0.00021)
LN(Electricity to Diesel Price)	-0.9078%* (0.51403)	-0.9568%* (0.50935)	-0.9122% (0.56809)		-0.808% (0.50849)
dLN(Electricity to Diesel Price)				-1.0351% (0.68256)	
mLN(Electricity to Diesel Price)				-0.8613%** (0.39653)	
Trend	2.5E+5%*** (70.504)	3.0E+5%*** (61.454)	2.9E+5%*** (64.762)		
dTrend				3.8E+5%*** (120.275)	7.3E+5%*** (58.816)
mTrend				omitted	omitted
Observations	251	251	251	251	251
Additional controls?	✓	X	✓	✓	✓
χ^2 -score	955.62***	582.79***	833.76***	2520.34***	1832.40***
Within R^2	0.7914	0.7907	0.7949	0.8081	0.8021
Between R^2	0.7579	0.7395	0.7231	0.8735	0.8590
Overall R^2	0.7747	0.7670	0.7606	0.8381	0.8287

Note: Country Random Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. Last three variables not reported as they are not important and significant.

*** p < 0.01

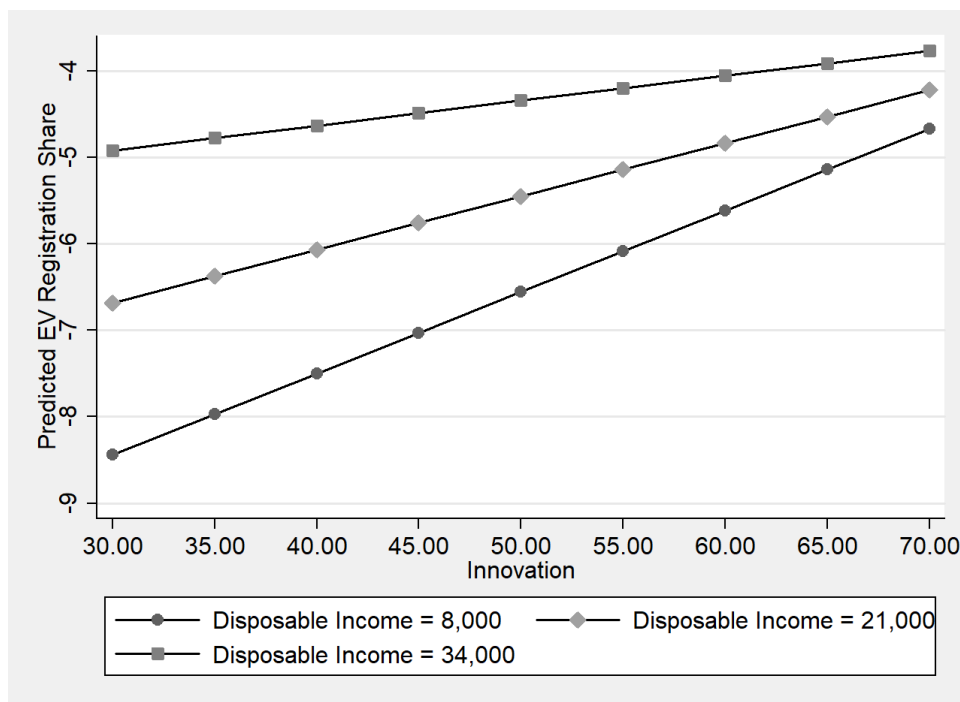
** p < 0.05

* p < 0.1

The results of the different regressions in Table 7.19 show that the interaction term *Inno.*DI* is insignificant in almost every regression. Only in the first hybrid model, the coefficient for the between-country effects exhibits a coefficient that is

statistically significant at a 10% level. Surprisingly, the coefficient is however not as expected positive but negative. The interpretation of the results of an interaction term that consists of two continuous variables is not as straightforward as the interpretation of an interaction between a continuous and a binary variable. It is suggested to explain the influence of the interaction term on the dependent variable with a visualisation that graphs the interaction of the two variables. Figure 7.4 attempts to illustrate the relationship between the two interaction terms and the dependent variable. The graph depicts the predicted EV registration rates, which are estimated based on the GTS regression model, for three different disposable income groups in relation to changes in the level of innovativeness. Since the interaction terms of all regressions have almost the same magnitude, the GTS model is selected as a representative to explain the behavior.

Figure 7.4: Interaction Term



For the disposable income groups it was decided to take values that are close to the sample minimum and maximum and a value that is in the middle of these values to capture the entire spectrum of potential movements and influences of differing innovativeness levels on the EV registration rate. As it can be seen in Figure 7.4, countries with a higher disposable income exhibit a higher rate of new EV registrations. However, focusing on the slopes of the graph that represent the

relationship between innovativeness and the ratio of new EV registrations, it can be noticed that while the slope of each disposable income group is positive, the slope is slightly higher for the group with the lowest value of disposable income. As disposable income increases, the slope becomes smaller. This would mean that, the wealthier people become in a country, the less influence innovativeness would exercise on the adoption behavior of EVs. Since, the coefficients of the interaction terms are however not significant in almost all models there is no evidence that the previously discussed effect is present on the market and a country's level of *Innovativeness* functions as a moderator on the relationship between disposable income and the registration rate of new EVs. Moreover, it can be argued that while the between estimate of the hybrid model might exhibit a statistically significant influence, the magnitude of the impact can be considered too small to have any practical significance. In conclusion, this investigation does not find evidence for the hypothesis of a moderating effect of a country's level of innovativeness, established in chapter 3.4.2.2

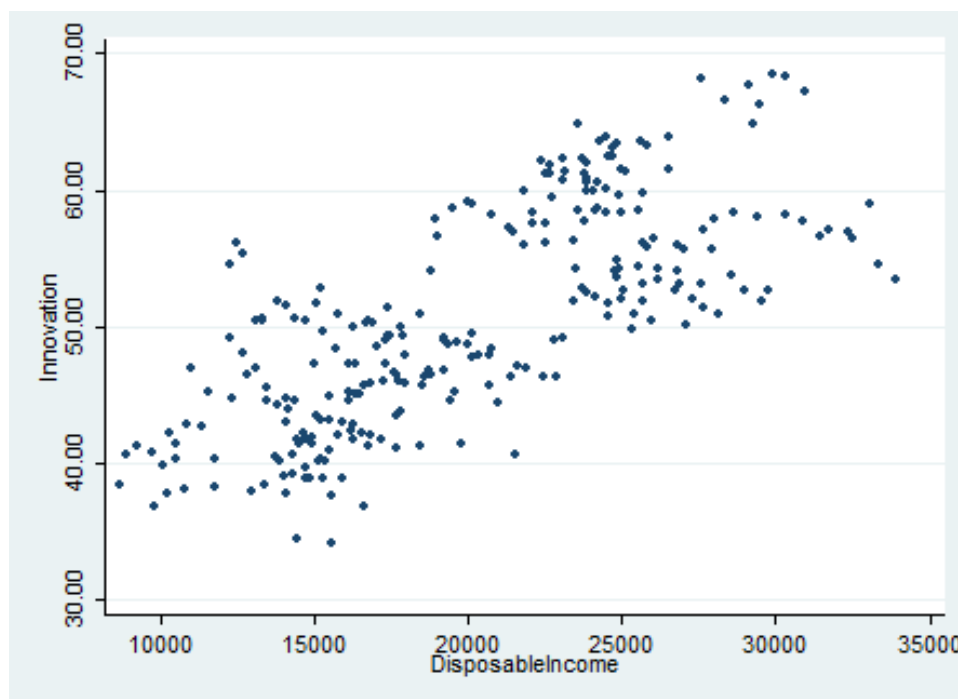
7.4.4 Innovativeness as a Mediator

After ruling out a moderating influence of a country's innovativeness level on the relationship between disposable income and the registration rate of EVs in the previous subchapter, it is now analysed whether country innovativeness might exhibit a mediating effect on the relationship between the independent and the dependent variables. The rationale behind the assumption of innovativeness as a mediating variable is that EVs, as it is normally the case with innovations that enter the market, are relatively expensive. Thus, countries or the citizens of a country that exhibit a higher purchasing power are more likely to purchase such a vehicle type. This assumption has already been verified in the previous subchapter with Figure 7.4, that shows a higher EV registration rate for the slope representing the countries with higher disposable income.

Moreover, as discussed in the literature review, it has been established that wealthier country's are more innovative. Evidence for this assumption is also provided by Figure 7.5 that graphs the relationship between disposable income and the corresponding innovativeness scores of the investigated sample countries. Thus, it is hypothesised that the purchasing power of a country will increase its innovativeness and this in turn will increase the likelihood of an EV purchase. Thus, the eventual reason why EVs are purchased is not simply because people,

corporations or the government can afford such a vehicle type but that they want to express their personality (innovativeness) with this behavior.

Figure 7.5: Relationship between Country Innovativeness and Disposable Income



To analyse this hypothesis, in a first step it has to be decided which of the three original models should be used for the mediation analysis. This decision is based on two tests; namely the Akaike's (AIC) and Bayesian (BIC) information criterion, that determine the quality of each of the three models and in contrast to the R^2 value take the number of regressors of the regression into account.

Table 7.20: Akaike's and Bayesian Information Criterion

Model	Obs.	ll(null)	ll(model)	df	AIC	BIC
All variables	251	-467.5938	-273.6972	12	571.3944	613.6998
Gen-Spec	251	-467.5938	-274.6471	9	567.2941	599.0232
w/o Chargers	251	-467.5938	-273.6977	11	569.3954	608.1754

The model with the lowest AIC and BIC value is obtained with the GTS model specification. Therefore, both tests indicate that the model specification with the lowest amount of relative information lost and hence the model that exhibits the best trade-off between goodness of fit and simplicity between these three alternatives is provided by the GTS specification. Consequently, it is decided to use this model specification for the mediator analysis.

For the mediation analysis itself, this study follows the approach of Baron and Kenny (1986) and applies three different regression models: in the first step the mediator variable is regressed on the independent variable. In the second step, the independent variable is regressed on the dependent variable, while in the last regression model both mediating and independent variable are regressed on the dependent variable. All models are specified with an RE specification. Thus, the following three equation models can be established for this analysis:

$$(7.4) \quad I_{it} = \alpha_1 + \beta_1 DI_{it} + \beta_2 S_{it} + \beta_3 CP_{it} + \beta_4 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_5 TR_{it} + \epsilon_{it}$$

$$(7.5) \quad \ln(EV)_{it} = \alpha_1 + \beta_1 DI_{it} + \beta_2 S_{it} + \beta_3 CP_{it} + \beta_4 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_5 TR_{it} + \epsilon_{it}$$

$$(7.6) \quad \ln(EV)_{it} = \alpha_1 + \beta_1 I_{it} + \beta_2 DI_{it} + \beta_3 S_{it} + \beta_4 CP_{it} + \beta_5 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_6 TR_{it} + \epsilon_{it}$$

Baron and Kenny (1986) claim that a mediation effect can be determined if certain conditions for the regressions are met. First of all, the independent variable must significantly influence the mediator variable in the first regression and the dependent variable in the second regression. Furthermore, in the third regression a significant influence of the mediator variable on the dependent variable needs to be present. Hereby, Baron and Kenny (1986) establish a concept of perfect mediation. A perfect mediation is when only the mediator variable is significant and the independent variable does not exhibit a significant influence on the dependent variable any longer.

For this investigation, the just described process is performed with the entire sample and with a slight modification of the sample. The modification takes on the form of an omission of the data for the country Norway. Reporting an EV registration rate of more than 55% in 2019 of all new car registrations, this product cannot longer be considered an innovative vehicle type in this particular country. In addition and more importantly EVs are due to high taxes on ICCs the cheaper car alternative (Norsk elbilforening, 2021) and thus people with a lower purchasing power should theoretically tend to purchase an EV if their purchase decision is largely determined by costs.

Table 7.21: Regression Results: Innovativeness as Mediator

Variable	Entire Sample			w/o Norway		
	Model 7.4 (Dep. = Innovativeness)	Model 7.5	Model 7.6	Model 7.4 (Dep. = Innovativeness)	Model 7.5	Model 7.6
Innovativeness			6.4044%** (0.02704)			7.7426%*** (0.02874)
Disposable Income	0.00032* (0.00017)	0.0143%*** (0.00003)	0.0083%** (0.00004)	0.00037** (0.00017)	0.0128%*** (0.00002)	0.0058% (0.00004)
Subsidies	-0.00008 (0.00007)	0.0103%*** (0.00002)	0.0099%*** (0.00002)	-0.00005 (0.00007)	0.0099%*** (0.00002)	0.0090%*** (0.00002)
Chargers 100km highway	-0.00069 (0.00111)	0.0087% (0.00015)	0.0206% (0.00024)	0.00067 (0.00146)	-0.0172% (0.00021)	-0.0392%* (0.00023)
LN(Electricity to Diesel Price)	2.0964 (1.52372)	-0.8372%* (0.50231)	-0.9014% (0.50400)	2.3848 (1.53880)	-0.6942% (0.49738)	-0.7638% (0.50190)
Trend	-57.501 (183.091)	2.0E+5%*** (58.7540)	3.0E+5%*** (61.7457)	-181.206 (205.579)	2.8E+5%*** (57.4797)	5.7E+5%*** (53.7744)
Observations	261	251	251	252	242	242
χ^2 -score	15.20***	721.74***	547.25***	16.14***	454.81***	524.77***
Within R^2	0.0322	0.7863	0.7909	0.0232	0.7868	0.7936
Between R^2	0.5161	0.6575	0.7285	0.5780	0.5783	0.7195
Overall R^2	0.4820	0.7270	0.7620	0.5432	0.7122	0.7669

Note: Country Random Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. This does not apply for Model 7.4 as the dependent variable is not log transformed. Thus, the interpretation is completely different. A unit increase of the independent variable causes now not a percentage increase in the dependent variable.

*** p < 0.01

** p < 0.05

* p < 0.1

Based on the results of the mediation analyses, that can be seen in Table 7.21, the variable *Innovativeness* fulfills all requirements of the Baron and Kenny (1986) approach to be considered a mediator variable between disposable income and EV registrations. While for both sample variations, the determinant *Disposable Income* significantly impacts a country's level of innovativeness (Model 7.4) and the EV registration rate (Model 7.5), this variable is also significant at a 5% level in Model 7.6 in the mediation analysis where the entire sample is considered. In contrast, *Disposable Income* becomes insignificant in Model 7.6 where Norway is omitted from the analysis, which means that a perfect mediation exists in this case. This supports the assumption that the EV market in Norway is in a more advanced stage compared to the other countries in the sample.

Since disposable income exerts a significant influence on the the variable *Innovativeness* an indirect effect stemming from the determinant *Disposable Income* over *Innovativeness* on the EV registration rate can be estimated. For the mediator analysis employing the sample that encompasses all countries this effect is 0.00205% ($0.00032 \cdot 6.4044\%$) and for the analysis omitting Norway the effect is with 0.00287% ($0.00037 \cdot 7.7426\%$) slightly higher. These values are not as small as they may initially seem when putting them in conjunction with the properties of the determinants and scaling the determinant *Disposable Income* on a 1,000 € basis. An increase of 1,000 € in the average disposable income of a country would therefore indirectly results in an increase of the EV registration rate by 2.87%. Hence, the coefficient is not only of statistical but also of practical significance. Thus, with this analysis initial evidence is found that supports Hypothesis 3.4. However, it is recommended to more thoroughly investigate a potential mediator relationship by employing a larger data set.

7.4.5 Robustness Tests

In the following several robustness tests are executed that should test the validity of the results obtained in this chapter. These robustness tests include one test where the trend variable is replaced by time dummies. Time dummies are a better method to control for universal shocks that have affected all countries in the investigated time period, however the inclusion of time dummies causes more losses in the degrees of freedom of the regression model. The second robustness test is the application of a different statistical model. In particular, the validity of the results are checked with a between estimator. Finally, as in the previous chapter, in this

analysis small car markets are excluded from the regression as another robustness test.

7.4.5.1 Time Dummies

In a first robustness test, the trend variable is replaced with time dummies for each except the first year considered in the investigation. The reason for not including a time dummy for the year 2011 is to avoid the dummy variable trap. With the inclusion of time dummies, a time fixed effects model is established that should account for universal shocks on the EV market, regardless of the country. The rest of the model specification is equivalent to the RE models, specified in Chapter 7.3.1.

Table 7.22: Regression Results: Time Dummies

Variable	All variables	Gen - Spec	w/o Chargers
Innovativeness	7.3441%** (0.03294)	6.1718%** (0.02937)	6.9014%* (0.03869)
Disposable Income	0.0110%** (0.00005)	0.0091%** (0.00004)	0.0103%* (0.00006)
Subsidies	0.0106%*** (0.00002)	0.0100%*** (0.00002)	0.0106%*** (0.00002)
Chargers 100km highway	0.0085% (0.00021)	0.0176% (0.00024)	
LN(Electricity to Diesel Price)	-1.1605%* (0.60387)	-1.2199%* (0.63149)	-1.2173%* (0.67600)
Dwelling House	-0.6033% (0.00697)		-0.5311% (0.00830)
Income 80 to 20	0.0893% (0.09605)		1.4576% (0.11793)
Home Ownership	1.8636% (0.01987)		0.9677% (0.02149)
Time Dummies	✓	✓	✓
Observations	251	251	251
F-score	1867.48***	1429.35***	1405.93***
Within R^2	0.8047	0.8052	0.8072
Between R^2	0.7461	0.7255	0.7191
Overall R^2	0.7768	0.7685	0.7659

Note: Country Random Effects model with robust standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. The Standard Errors are reported in brackets.

* $p < 0.01$

** $p < 0.05$

*** $p < 0.1$

As it can be seen in the results of the robustness test reported in Table 7.22, the estimate of the *Innovativeness* determinant is still significant for all models, thus supporting the results obtained in the main part of the investigation. Only in the model in which the charging infrastructure determinant is omitted a loss in significance can be recorded for the variable *Innovativeness*. Nevertheless, the estimate is still significant at a 10% level. Moreover, as previously discussed,

accounting for the development of the charging infrastructure is important in the analysis. Looking at the estimated marginal effects of the main independent variable, the magnitude of the coefficients have only slightly decreased when comparing them to those of the regressions with the trend variable. In addition, the significance and estimates of all variable coefficients in general have only marginally changed if they have changed at all. Hence, the inclusion of a trend variable in the main part of the analysis to save degrees of freedom in the regression seems justified.

7.4.5.2 Between Estimator

In a second robustness test the statistical method for the analysis is altered to a Between-Effects model. A Between-Effects model reduces the considered sample size as it only considers the group means of all variables in the regression. Consequently, this statistical approach takes advantage of the variation between the groups, in the case of this investigation between the countries, to obtain estimates for the determinants. According to Blaydes (2006) a Between-Effects model is one of the most conservative model specifications since only rarely statistically significant estimates for the variables are obtained due to the small sample size.

All three model alternatives are regressed with a Between-Effects model, employing a Jackknife resampling approach for bias correction. A Jackknife resampling approach is applied instead of bootstrapping as it is more suitable for a small sample (Riveros Gavilanes, 2020). Moreover, in contrast to the bootstrapping approach it always provides the same results for the standard errors. These values differ when applying bootstrapping as a resampling approach as it draws random samples from the data set at hand (Sinharay, 2010). The results for all model alternatives presented in Table 7.23 provide evidence of a significant and positive influence stemming from a country's innovativeness level on EV registration rate. The results can be considered a strong support for the findings of the main part of the investigation, as even with such a conservative estimation approach *Innovativeness* remains to be one of only two significant determinants of the EV market when comparing differences between the countries. When recalling the results obtained from the hybrid model, the significant outcome of the main independent variable is however not surprising. As previously discussed, a hybrid model breaks up the variables into its within- and between effects. Therefore, the between effects estimates of the hybrid model, which are also based on the group

means, more or less mirror the estimates of the Between-Effects model.

Table 7.23: Regression Results: Between Estimator

Variable	All variables	Gen - Spec	w/o Chargers
Innovativeness	6.7285%** (0.03166)	5.8923%** (0.02226)	8.9471%** (0.03217)
Disposable Income	0.0061% (0.00005)	0.0054% (0.00003)	0.0124% (0.00009)
Subsidies	0.0063% (0.00007)	0.0045% (0.00004)	0.0117% (0.00011)
Chargers 100km highway	0.2014%*** (0.00054)	0.2034%*** (0.00048)	
LN(Electricity to Diesel Price)	-0.5951% (0.64826)	-0.7615% (0.54794)	-0.8475% (0.75428)
Trend	754.901% (730.59)	678.909% (435.67)	109322% (800.06)
Dwelling House	-0.5909% (0.01170)		-0.8533% (0.01248)
Income 80 to 20	5.5765% (0.13431)		-0.9580% (0.16362)
Home Ownership	0.7581% (0.02110)		4.0637% (0.03689)
Observations	251	251	251
χ^2 -score	15.43***	20.72***	6.32***
Within R^2	0.5720	0.5514	0.7863
Between R^2	0.8631	0.8562	0.7505
Overall R^2	0.6800	0.6626	0.7682

Note: The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. The Standard Errors are reported in brackets.

*** p < 0.01

** p < 0.05

* p < 0.1

7.4.5.3 Exclusion of Small Car Markets

As in the investigation of EA and its influence on the EV market, in this robustness test all countries that do not exceed 30,000 new car registrations in one of the considered years, are excluded from the analysis. Eliminating small car markets from the investigation provides information whether the leverage effect, which could arise due to an equal weighting of each group in a panel data model, could have significantly influenced the estimates of the main part of the investigation. This is important to test, because small divergences in the number of registered EVs have a stronger influence on a small car market, wherefore anomalies could bias the results.

Excluding Estonia, Latvia, Lithuania and Malta from the analysis in this robustness test, the significant influence of country innovativeness on the EV registration rate is tested with an FE, RE and three different hybrid models. While in the first hybrid model all variables are decomposed in their within and between effects, in the second hybrid model only those variables that exhibited a significant difference in their within- and between effects coefficient, tested with an augmented regression, remained decomposed. In the third hybrid model only the variable *Innovativeness* received an RE specification. Reporting the results of these five different model specifications ensures the comparability with the results obtained from the regressions of the main part considering all countries in the data set. Again, in regard to the considered variables in the regressions, only the results for the model including all control variables is reported in Table 7.24. The results for the other GTS as well as the model excluding the charging infrastructure can be found in Appendix F.

Looking at the results of the main independent variable, the determinant exhibits significant coefficients for each of the applied statistical approaches. Even the within estimates obtained from the FE regression as well as the hybrid model turn out to be significant at a 10% level. Moreover, the magnitudes of the coefficients are only marginally smaller than those obtained from the regressions including all countries. In general, the significance as well as the approximated marginal effects of all variables are similar to those of the main part of the analysis. Therefore, a too severe leverage effect on the estimates stemming from the small car markets can be ruled out and further support for the significant influence of country innovativeness on the EV market is provided.

Table 7.24: Regression Results: Exclusion Small Car Markets

Variable	Baseline Regressions		Hybrid Models		
	FE	RE	Hybrid	Hybrid Final	Hybrid Final Only Inno. RE
Innovativeness	4.0897%* (0.02190)	5.6249%*** (0.01886)		4.0739%** (0.01830)	4.9081%*** (0.01667)
dInnovativeness			4.0897%* (0.02233)		
mInnovativeness			5.4777%** (0.02191)		
Disposable Income	0.0079% (0.00007)	0.0128%** (0.00006)		0.0050%* (0.00003)	
dDisposable Income			0.0079% (0.00007)		0.0080% (0.00007)
mDisposable Income			0.0043% (0.00003)		0.0046%* (0.00003)
Subsidies	0.0082%*** (0.00002)	0.0099%*** (0.00002)		0.0087%*** (0.00002)	
dSubsidies			0.0082%*** (0.00002)		0.0083%*** (0.00002)
mSubsidies			0.0095%** (0.00004)		0.0096%** (0.00004)
Chargers 100km highway	-0.0667%*** (0.00014)	-0.0084% (0.00019)			
dChargers 100km highway			-0.0667%*** (0.00014)	-0.0687%*** (0.00017)	-0.0660%*** (0.00017)
mChargers 100km highway			0.2067%*** (0.00025)	0.2145%*** (0.00015)	0.2073%*** (0.00026)
LN(Electricity to Diesel Price)	0.1000% (0.28902)	-0.0989% (0.31551)		0.0769% (0.29865)	
dLN(Electricity to Diesel Price)			0.1000% (0.29472)		0.0840% (0.29793)
mLN(Electricity to Diesel Price)			-0.0727% (0.38460)		-0.0815% (0.39658)
Trend	8.7E+5%*** (83.650)	3.8E+5%*** (67.273)			
dTrend			8.7E+5%*** (85.301)	1.2E+6%*** (52.706)	8.3E+5%*** (84.480)
mTrend			omitted	omitted	omitted
Additional Controls?	✓	✓	✓	✓	✓
Observations	219	219	219	219	219
F/ χ^2 -score	94.18***	1257.93***	9331.71***	3605.48***	8504.49***
Within R^2	0.8754	0.8660	0.8754	0.8738	0.8753
Between R^2	0.4747	0.7677	0.9097	0.9047	0.9095
Overall R^2	0.6619	0.8180	0.8913	0.8880	0.8912

Note: Country Fixed and Random Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. All hybrid models are based on an RE specification.

*** p < 0.01

** p < 0.05

* p < 0.1

7.4.6 Discussion of Results

In line with the findings of previous research (Jansson, 2011; Morton et al., 2016; Wang et al., 2018; Schlüter and Weyer, 2019) focusing on EV adoption intention, the results of this study provide evidence for the significant influence of innovativeness on the EV market on a macroeconomic level. Moreover, a potential mediating

function of country innovativeness between the relationship of wealth and the EV market is uncovered.

Interpreting first the estimates for the country innovativeness determinant from the different statistical approaches, the coefficients approximated with an approach that considers the variation between the countries exhibits higher statistical significance. In particular, while the estimates of this determinant from the RE, Hybrid and Between-Effects model are significant at a 1% or 5% level, they loose in significance when solely relying on the within variation of the countries. In case of the GTS specification with the data fitted in an FE model, country innovativeness even turns out to be not significant at all. This outcome has influences on the interpretation of the results. The results should therefore primarily be interpreted in the sense that more innovative countries exhibit a higher registration rate of EVs. On the contrary, one should be cautious to interpret the results in the way that when less innovative countries become increasingly innovative they will also notice an increase in the registration rate of EVs, although, weak statistical proof has also been found to allow this conclusion. This does not pose a concern for this study since country innovativeness is as already pointed out a sluggish determinant and less innovative countries did not suddenly become innovative countries in the investigated time period. Focusing on the magnitude of the obtained coefficients for this variable, according to the results a country with a 1 unit higher value for innovativeness exhibits a higher EV registration rate in the range of 5.5% to 8% if everything else remains the same. Considering the low variation of inventiveness within and between the countries, which can be based on the geographic proximity of the analysed countries as well as when looking at the magnitude of the coefficients of the control variables, the approximated marginal effects of country innovativeness seem reasonable. The estimates for the variable *Subsidies* for example suggest that a 1000 € raise in the granted amount of subsidies in a country would approximately lead to an increase in the registration rate of EVs by about 10%, which is only marginally higher than the influence of country innovativeness. It should however be kept in mind that innovativeness is a psychological factor and there is no 100% objective measurement for such a determinant, wherefore the coefficients should be interpreted cautiously. The estimates can differ based on the applied surrogate that is used to measure a country's level of innovativeness. Nevertheless, in this study it is argued that the GII is the best gauge for country innovativeness that can be applied in this investigation, as it entails information

about the three potential customer groups of this vehicle type as well as how supportive of innovation the environment is. Based on the findings it can however be concluded that country innovativeness has a significant positive influence on the adoption of EVs and is indeed an important determinant of this market.

When putting the findings of this investigation in context with previous research (e.g. Plötz et al., 2014; Morton et al., 2016; He et al., 2018; Schlüter and Weyer, 2019), which has found that innovativeness on a personal level makes EVs more appealing to an individual, they confirm the significance of this determinant on a macroeconomic level. It needs to be taken into consideration that while previous research usually considered the individual's level of innovativeness, this research extends the scope of analysis and supplements the findings by looking at innovativeness on a societal level. It therefore provides evidence that not only the innovativeness of the three customer groups is a decisive factor but that also the advantages an innovative environment entails, such as a sophisticated market as well as infrastructure, can accelerate the diffusion of this technology. Furthermore, by taking on this macroeconomic perspective, from the results it can be derived that people that live in an innovative environment might feel the pressure to behave more innovatively themselves. Because of the high visibility of cars, the purchase of an EV is an efficient way for an individual to express its social status and innovativeness. Hence, this study could also be seen to provide evidence for the social norm dimension of the TPB. The application of an index for innovativeness that does not depend on a self assessment of the innovativeness level by an individual as in previous research in general helps to broaden the understanding of this determinant and illustrates that innovativeness can foster the market through different mechanisms. Moreover, employing a macroeconomic perspective in this investigation helped to eliminate the doubts emerged in previous studies, that are based on the attitude-action gap, whether innovativeness influences actual purchase behavior. The significant results for the country innovativeness variable imply that despite several market barriers which could have prevented the citizens, companies or governments from the purchase of this vehicle type, this determinant does not only influence the intention to purchase an EV as discovered in previous research but influences the actual sales ratio of EVs as well. Consequently, in contrast to the altruistic determinant EA, no evidence for the existence of the attitude-action gap for the more self-centered driver innovativeness is found, at least not to the extent which makes this factor insignificant.

As opposed to what was assumed in the second hypothesis in Chapter 3.4.2.2, no significant moderating influence of country innovativeness on the relationship between wealth and EV registration is detected. Hence, no support is found for the assumption expressed by Al-Jundi et al. (2019) that countries with wealthy and innovative citizens adopt EVs faster than countries with wealthy and less innovative citizens. However, in this case a potential downside could be the macroeconomic perspective applied in this investigation. The sample consists of only 29 countries which do not exhibit strong variations in neither the innovativeness level nor the wealth of the population. Moreover, wealthier countries also commonly exhibited a higher level of innovativeness in the sample, wherefore differences between these determinants are not present for a sufficient number of observations. Thus, using a larger sample, which can also be collected by means of surveys, might provide a different result for the moderator analysis. Building on the observation of a potential relationship between wealth and country innovativeness however, it can be interpreted as a first indication of a mediation effect of innovativeness between wealth and EV adoption as suggested in the last hypothesis of Chapter 3.4.2.2. This mediation effect was also empirically validated in this investigation, contributing to the understanding of the significance of the influence of wealth on innovativeness in general as well as the ways it influences EV adoption in particular. At first it provides further support for Rogers (2003) characterisation that wealthy people are more likely to be innovative as they are less risk averse. In particular, it contributes to the stream of research that explicitly deals with uncovering the determinants of innovativeness on a macroeconomic level (Dekimpe et al., 2000; Tellis et al., 2003). For the stream of research focusing on determining the drivers of the EV market, it extends the knowledge in regard to how a country's and its citizens' wealth indirectly influences the adoption of EVs. This research, thereby, extends the list of identified determinants that mediate the relationship between wealth and EV adoption by an additional factor. In a first attempt Rietmann and Lieven (2019) already found out that the purchasing power of a country's citizens influences the granted amount of subsidies, traffic priorities as well as charging infrastructure for EVs and therefore indirectly influences the purchase behavior of this vehicle type. Country innovativeness, as detected in this research, therefore supplements the list of identified mediating determinants, which leads to the assumption that the wealth of a country's citizens is more important than initially assumed. Considering that EVs are a technology which can be categorised in the high-price segment,

the importance of wealth becomes even clearer as a certain level of prosperity is required to be able to afford such a vehicle. The insignificant direct influence of the variable *Disposable Income* on EV registration rate obtained from the FE models in Chapter 7.4.1, could be traced back to the sluggish variable properties of this determinant. Several studies applying a within estimator for the approximation of the influence wealth has on the EV market detected an insignificant relationship as well (Wee et al., 2018; Münzel et al., 2019; Li et al., 2019). This does not pose a problem if this variable is not the one of interest and is only considered as a control variable, however, emphasises the problem with the efficiency of such estimators for variables that exhibit a low within variation in the observations. On the other hand, keeping in mind that the geographic scope of analysis encompasses the European Union and therefore almost exclusively developed countries, which means that the average incomes of the households are quite similar across the countries, a significant coefficient obtained with an RE model provides evidence that wealth is indeed an important determinant of this market. Contemplating the determinant wealth from a logical causal perspective, it can be assumed that a purchase decision of an EV is not made because people have money to spare. This could imply that there are more factors that might mediate the influence between wealth and EV adoption, to be uncovered by future research.

After explaining and putting the results of the investigation into context with previous research, possible implications for practice are discussed in the following. The first implications strongly orientate on the DOI theory developed by Rogers (1962) and focus on how less innovative countries could accelerate the adoption of EVs in their local market. In particular the recommendations focus on highlighting the five main innovation characteristics that influence the adoption of an innovation discussed in Chapter 3.2.1.3, namely *relative advantage*, *compatibility*, *complexity*, *trialability* and *observability*. Since country innovativeness turns out to be a significant factor, a better communication as well as providing opportunities where people themselves can perceive whether EVs incorporate these key characteristics in less innovative countries might accelerate the diffusion of the product in these countries as well. This can be assumed as innovative people perceive these characteristics more strongly and faster, wherefore less innovative individuals need to be more convinced about the advantages this technology entails to dismantle their concerns (Rogers, 2003). This goes along with the risks individual's perceive from the adoption of EVs, which is one factor that makes more innovative people faster adopters

of a new technology. By addressing how an EV incorporates the five essential characteristics of an innovation, it could also contribute to a reduction of the perceived risks which prevent the adoption of this new technology. The communication of the first characteristic which is relative advantage is crucial, as customers need to be aware that the new product incorporates significant improvements compared to the current alternative products on the market. Consequently, countries as well as car producers should focus on communicating the advantages of EVs compared to ICCs. A relative advantage for example could be the lower emissions of the EVs and the resulting improvements in air quality. Further relative advantages could be the reduced fuel costs for an EV and the better acceleration (Peters and Dütschke, 2014; Plötz et al., 2014). This also calls on the car manufacturers to engage even more in the research of this product so that the advantages become more prevalent and thus become clearer to less innovative people as well. It further requires politics to support these research endeavours by for example granting additional subsidies. The second factor is compatibility. For some people sustainability for example is becoming an important value. As determined in the first research question EA in the time frame from 2010-2017 was not a significant determinant of EV purchase decisions, however, once the market barriers for EVs are reduced it is expected that EA might play a more decisive role. It could therefore be beneficial in the long run, to communicate the compatibility of EVs with this value. The complexity of this product appears not to pose a significant challenge at this point as only the engine of the car is changing. However, it might for example be useful to increase the ease of charging, as this is the core difference in usage compared to ICCs (Rezvani et al., 2015). A positive impact could be potentially achieved by standardizing charging plugs (Hall and Lutsey, 2017). Another factor that can accelerate the adoption of new technologies is the opportunity to test them. The trialability of EVs could for example be improved by adding more EVs into car sharing fleets as Schlüter and Weyer (2019) found a higher acceptance rate of EVs when people had access to them via car sharing companies. This will also enhance the observability of this technology, which represents the last important characteristic of an innovation. Improvements in the presentation as well as offering test drives at car dealerships would also lead to a better trialability and observability of this product and should therefore promote its diffusion in the market. Matthews et al. (2017) have also found that EVs were only rarely displayed in car dealerships, making it difficult for customers to familiarise themselves with this product and compare it to possible

alternatives. Moreover, it was found that car dealerships even discourage potential customers from the purchase of an EV (de Rubens et al., 2018).

These are only a few ideas, how politics as well as car manufacturers could enhance the perception of EVs of individuals. In general, policies and actions should be taken that aim to better communicate, improve car attributes or create an environment to experience the five key characteristics of innovations discovered by Rogers (1962) for EVs. This, especially applies to less innovative countries as the natural diffusion of EVs proceeds slower than in innovative countries because people are more risk averse in these countries.

Drawing on the findings of the mediator analysis, different implications for practice can be established as well. As found out by Rogers (2003) on individual level and later validated to be an important determinant also on a macroeconomic level by for example Dekimpe et al. (2000) or Tellis et al. (2003), wealth has a significant positive influence on innovativeness. This is because people are more inclined to take risks if they are wealthier as they can financially better cope with losses. Arriving at the same conclusion that wealth influences innovativeness and therefore indirectly the EV market, it is hypothesised in this study that EVs become more of an alternative for poorer countries in the secondary market. With advancements in research and development of EVs and subsequent decreasing vehicle prices of this car type, the adoption of such a vehicle poses a lower risk. Based on this argumentation, a general recommendation for companies developing technologies that can be categorised into higher price segments is to first introduce the products to markets that are wealthy and exhibit a high level of innovativeness. This can lead to a faster diffusion of the technology, resulting in higher revenues that can be spent for further improvements of the innovation. Hence, country innovativeness turns out to be a location factor that should be considered for initial market penetration. Another potential idea that could foster the EV market and is based on the findings of the mediator analysis is to establish a global infrastructure fund, governments of poorer countries can use to for example develop a charging infrastructure. A well developed charging infrastructure minimises the risk EVs entail and therefore reduces the influence of the level of an individual's innovativeness. The establishment of such a fund could be in the interest of every nation as climate change poses a global threat, wherefore every country needs to make a turn around to a more sustainable transportation mode as quickly as possible.

Similar to the analysis of the previous chapter, this research is also not free of limitations. These limitations can however in turn be used as avenues for future research. First of all, this study applies a general understanding of innovativeness. As pointed out by different researchers (Hoffmann and Soye, 2010; Morton et al., 2016), the innovativeness level of an individual might be domain specific and therefore could attract the attention about innovations in a few markets and lead to neglecting completely different markets. This could mean that an individual that is in general innovative might not be defined as innovative when considering the automobile sector and vice versa. Although, it was found in this investigation that on macroeconomic level a general higher level of innovativeness already leads to a faster adoption of EVs, it could therefore also be of interest to employ a measurement of innovativeness that is sector focused. In case country's that are particularly innovative in the automobile sector adopt EVs faster than other innovative countries, more refined target location decisions can be made by EV manufacturers. As this research is however to the best of my knowledge the first that investigated the influence of innovativeness on the EV market on a macroeconomic level, this research focused on developing an overarching understanding how general innovativeness can influence the EV market. Moreover, analysing the influence of subject dependent innovativeness could be more suitable for investigations on individual level.

The second limitation of this study is that a broad measurement of innovativeness is applied which is however also a consequence of the macroeconomic perspective and data availability. As a result, it can for example not be determined whether the innovativeness level of the citizens, companies and government or the innovative environment is the more important factor. Furthermore, since EV registration data is only available on an aggregated level and no distinction between customer groups is made, it is not possible to determine the precise effect of innovativeness of the citizens, companies and government on EV adoption.

Finally, it should be kept in mind that innovativeness is like EA a psychological determinant, wherefore no precise measurement exists and the application of different measures leads to a more comprehensive picture of what the actual influence is. Consequently, a recommendation for future research is to repeat this study, applying a different measurement of innovativeness.

7.5 Conclusion

In this chapter of the dissertation, the influence of country innovativeness on the EV registration rate was analysed. Using actual market data of 29 different countries over a nine year time period spanning from 2011 to 2019, it is to the best of my knowledge the first study that took on a macroeconomic perspective to analyse the significance of this relationship. In contrast, previous studies focusing on this research question relied on surveys as a data collection method and predominantly looked at whether innovativeness influences an individual's intention to adopt an EV. Consequently, the findings of previous studies are limited to innovativeness on an individual level and might be biased due to the attitude-action gap the existence of which has been uncovered in this market by various researchers. The significance of this factor, determined by previous research, was however verified in this research context. Moreover, it has been uncovered that innovativeness also exhibits a mediating influence on the relationship between wealth and EV adoption. This research thereby contributes to extant literature in various ways. It does not only confirm the findings of studies on individual level but also suggests that an innovative environment might be important as well. Since the considered variable aggregates the innovativeness of the three potential customer groups of EVs in a country (citizens, companies and government) as well as prerequisites for an innovative environment in one overall score it does not allow to precisely determine the specific effect of innovativeness from each customer group on the EV market. As registration rates of EVs for the different customer groups are not available on such a detailed level, an investigation of this research question was not possible with the applied research setting and therefore presents an opportunity for future research when data availability has improved. Based on the findings, important implications for politics as well as car manufactures were derived. Amongst others, it has been concluded that country innovativeness is an important factor for a company to consider when deciding where to first introduce a high-cost technology and therefore which market should be penetrated first.

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The results of the previous investigations have shown that while the altruistic factor EA does not significantly influence the EV market, the more self-centered value innovativeness seems to be an important market driver. A potential explanation for the insignificant influence of the altruistic factor EA on the EV market is, as discussed in chapters 3 and 6, potential market barriers that hinder the adoption of this vehicle type based on such a motivator. Thus, the question arises how can these market barriers be overcome, so that not only self-centered but also altruistic factors play a decisive role for the development of the EV market. Identified by previous research, one major barrier that prevents the more widespread adoption of EVs is the higher costs of an EV compared to an ICC. As a reaction to this negative price gap and as they are considered to be a potential solution, especially in the early years after market introduction, a multitude of governments grant subsidies for the purchase of an EV.

Thus, the efficiency of subsidies in the European region is investigated in this chapter. To analyse the effect of subsidies on the EV market different statistical approaches that are able to process panel data are applied. It is further distinguished between different types of incentives such as incentives that are granted at the point of sales or which are annually recurring, to uncover potential differences in their efficiency. Moreover, to obtain insights about how well subsidies are received

in regard to differences in the type of electric vehicle, analyses for the cumulative EV market and the individual BEV and PHEV markets are performed.

The results of the investigation complement the findings of the investigation of Münzel et al. (2019) and provide further interesting new insights about the relationship between subsidies and the EV market. First of all, employing a larger data set than that of Münzel et al. (2019) and thereby covering the most recent years of this market, the results for the aggregated EV market confirm the significant positive influence of subsidies on the market. Interestingly, when looking at the BEV and PHEV market individually, a significant and positive influence stemming from subsidies are only found for the BEV type and not for the PHEV type when considering the entire time period from 2010 to 2020. Rerunning the regressions with a shorter time frame however yielded a significant influence of subsidies on the PHEV market too, providing evidence for the hypothesised diminishing influence of this policy measure. Furthermore, by applying a dynamic panel data approach, this study is able to account for the natural diffusion of this technology. Accounting for this factor it is shown that the influence of subsidies could be slightly but not severely overestimated.

8.1 Electric Vehicle

An excellent research about the influence of subsidies on the registration rate of EVs in a European setting has already been undertaken by Münzel et al. (2019). Although, the researchers have already investigated the influence of this determinant on the EV market, as discussed in the literature review, this research nevertheless provides some novelty to this strand of research. As EVs are a new technology, the influence of determinants can change over a short period of time as the market is evolving quickly. This requires to frequently repeat studies to assess the magnitude of the change and maybe even detect structural breaks in the relationship of the variables. Moreover, this study contributes to extant research by estimating the coefficients of the subsidies variables with a more conservative approach in form of a dynamic panel data model. Applying such an approach helps to account for potential endogeneity bias and should therefore exhibit estimates that are closer to the true population.

8.1.1 Descriptive Statistics

Different to the previous chapters, not a general analysis of the descriptive statistics is the first step in this investigation but a focus is directly laid upon the different types of subsidies, which represent the main independent variables of this study. To illustrate the amount of subsidies that are issued by the different countries over the investigated time period, Figure 8.1 is prepared. These graphs depict the amount of subsidies, broken down into the specific kinds of subsidies, calculated as described in the methodology section in Chapter 4. The final step described in the data cleansing process, which is the deletion of the values when subsidies are negative is however, not applied and thus not considered in the graphs of Figure 8.1. This allows the analysis of the efficiency but also the weaknesses of several subsidy policies granted in different countries.

Figure 8.1: EV Subsidies with Negative Amounts



Note: Structure of the illustration is based on Münzel et al. (2019). Focus of this graphic should be on the negative amount of subsidies. Since a continuous scale is used to present the amount of subsidies in the graphics, amounts that are close to 0 might also be illustrated in white. Therefore, it is recommended to also refer to the graphic that depicts the amount of subsidies where negative values have been eliminated to obtain a clearer picture of the amount of subsidies.

Looking at the values of the subsidies, especially for the countries *Greece, Poland and Cyprus*, the question arises how policy measures that are supposed to grant benefits to more sustainable vehicle types actually exhibit negative values and therefore even might disincentivise the adoption of such cars. The answer to the question is strongly correlated to the approach used to measure incentives and therefore what people perceive as an actual incentive to purchase an EV. As argued in this investigation, a policy measure provides an incentive when for example the amount of the costs of a tax are lower for EVs than for comparable ICCs. In particular, this means an incentive exists when the difference between the costs for a tax of a comparable ICC and an EV is positive. The different reasons why this study favours this approach for the determination rather than the approach that would calculate the difference between the amount of taxes that would apply to EVs with and without the incentives, are discussed in Chapter 4. The most important one is, however, that these special treatments are supposed to encourage the shift from the purchase of an ICC to an EV. Consequently, in this study it is assumed that only incentives which in a direct comparison provide an advantage above ICCs can make EVs a more attractive alternative.

This is the point where weaknesses of several incentives that are supposed to encourage the purchase of environmental friendlier cars become evident. Negative incentives do not emerge because governments grant direct subsidies for the purchase of an EV at the point of sales but levy taxes that are based on different vehicle attributes. When the CO_2 based component or the rate of the granted tax rebate for EVs cannot sufficiently weigh up the disadvantages of EVs for the other car attributes that are considered in a tax, the incentive (based on this calculation approach) does not exhibit the aspired influence. In Poland for example, the VAT exhibits negative values for the years 2018 and 2019, which means that customers would have to pay a higher VAT for the purchase of an EV than for a comparable ICC in these years. When looking more closely at this example, at first it has to be noted that the VAT is considered as a potential incentive because it includes a component in its calculation that provides advantages for the purchase of an EV. In particular, the VAT in Poland is calculated in these years as follows:

$$VAT = (V + T + E) * 23\%$$

where V represents the customs value of a car, T the tax value that only applies to vehicles that are imported from outside the EU and E is the Excise tax (ACEA, 2019). For the component mentioned last, the polish government permits an exemp-

tion for BEVs as well as PHEVs. Although, BEVs and PHEVs received a reduction in the Excise Tax, the total amount that is due for the VAT is still significantly higher for EVs than for comparable ICCs. Since according to the calculation of the VAT price, the vehicle price is the only other factor that influences the amount, the reason why this particular tax is more expensive for EVs can be traced back to the large price difference between EVs and ICCs.

Moreover, when looking at the amount for the point of sales (POS) tax, Figure 8.1 shows that the Excise Tax itself exhibits a negative value in the year 2020. This is due to a change in the tax rate that is applied to the vehicle value of PHEVs. Only PHEVs that incorporate an engine size below 2,000cc are still exempt from this tax. However, for PHEVs with an engine size above this threshold a reduced tax rate of 9.3% applies. Although, PHEVs receive a reduced tax rate, the tax rate applied in this case is still higher than that of a comparable ICC. The explanation for this phenomenon lies in the difference of the engine size of the vehicles considered in this investigation. While the ICC exhibits an engine size smaller than 2,000cc, the comparable PHEV incorporates an engine size greater than 2,000cc. Thus, it can be assumed that to counteract the substantially higher weight due to the incorporated batteries of the PHEV, this vehicle type requires a larger motor to achieve similar performance as the comparable ICC.

Another example that illustrates the problem where the subsidised environmental component cannot outweigh the disadvantages of another car attribute that is included in a tax calculation is the registration tax in Greece. The registration tax is calculated based on the list price of the car multiplied by a basic coefficient that depends on the propulsion of the vehicle and its retail price. This result is then multiplied with a component that takes into account the CO_2 emissions of the vehicle. While the taxable amount is 0 for the BEV due to a 0% value of the basic coefficient, the taxable amount for the PHEV model is despite several reductions substantially more expensive than for the comparable ICC due to the substantially higher list price.

Thus, a crucial component that is often considered in the calculation of taxes is the price of a vehicle. Since, there is a large price gap between EVs and their comparable ICCs, some incentives that are granted are not sufficient to negate this price gap, wherefore some taxes for EVs are still higher than for comparable ICCs. Several taxes also depend on for example the kerb weight of a vehicle (e.g. the power tax in Finland). Since PHEVs and BEVs incorporate a large amount of

batteries, these vehicle types are generally heavier and therefore exposed to higher taxes. To circumvent this particular issue, Norway and Sweden have established approaches for the calculation of incentives that consider vehicle differences and therefore take disadvantages of EVs into account. In Norway for example, the reported weight of PHEVs is reduced by 23% for the calculation of the import tax. For the calculation of the company car tax, the government of Sweden accounts for the higher prices of an EV by using the price of a comparable ICC instead of the actual EV price as a basis for the calculation of the benefit in kind an employee receives. An additional reduction of 40% of the benefit in kind value is then also applied to lower the taxable amount (ACEA, 2020).

Although, this particular data set is not further employed for the remainder of the main analysis, its investigation has drawn the attention to, as well as helped explaining, the weaknesses of the development of taxes when it comes to accelerating the adoption of EVs.

As argued previously in the methodology section, it has been decided to process the data in terms of eliminating negative incentives. In this study it is argued that if a potential incentive emerges as negative, customers do not obtain any advantage of this incentive and therefore neglect it. The resulting influence of the data cleansing process can be seen in the descriptive statistics reported in Table 8.1. The minimum of each incentive does not fall below 0. This process, has of course also an influence on the means and standard deviations of the considered incentives. As the possible range of values an incentive can obtain has been limited, the values cannot vary that strongly anymore, which reduces the standard deviations of these variables. Moreover, the prohibition of negative values increases the mean of the variables. The effect this data cleansing process has on the variables is however not extensive as only a few countries exhibited negative incentives in some years of the investigated time period.¹ The amount of subsidies granted by each government and the development of the incentives policies over time can be deduced from Figure 8.2.

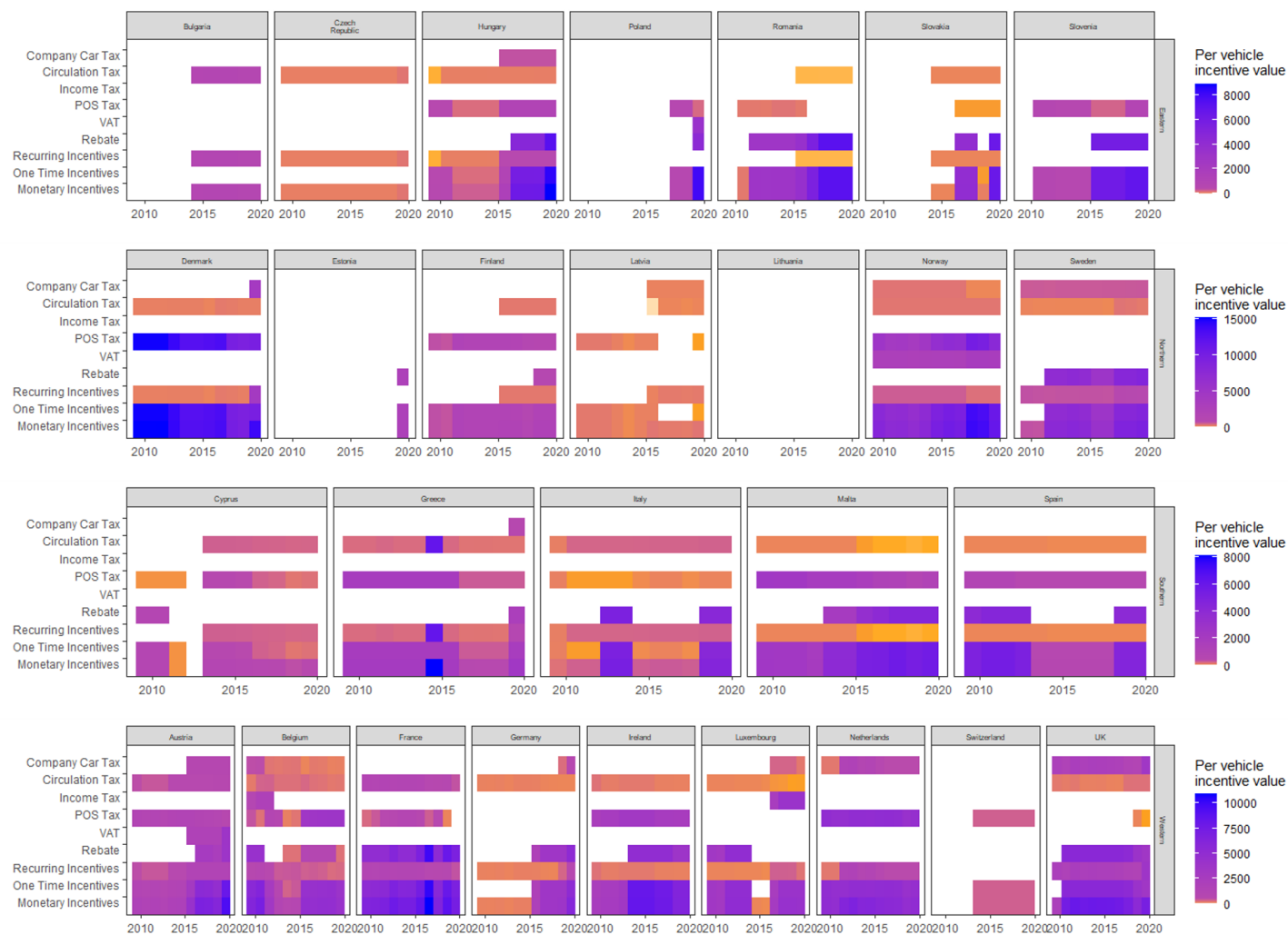
¹The descriptive statistics of the subsidies where negative values are allowed are reported in Table G.1 of Chapter G. The results support the claim that the processing of the data had no strong influence on the variables.

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Table 8.1: Descriptive Statistics: EV Market

Variable		Mean	Std. Dev.	Min	Max	Observations
EV Registration Share	overall	0.0246819	0.072923	0	0.745	N = 319
	between		0.0493936	0.0025858	0.2679648	n = 29
	within		0.0543576	-0.2401989	0.501717	T = 11
Subsidies	overall	3500.989	3677.193	0	15123.85	N = 319
	between		3207.524	0	13141.52	n = 29
	within		1886.019	-2394.764	10739.13	T = 11
One-Time Subsidies	overall	3171.789	3480.145	0	14984.63	N = 319
	between		3013.441	0	12635.72	n = 29
	within		1821.027	-2675.031	10409.93	T = 11
Rebate	overall	1598.258	2430.984	0	9900	N = 319
	between		1824.686	0	6177.273	n = 29
	within		1638.567	-4248.562	6970.985	T = 11
VAT	overall	219.6326	822.2552	0	4084.536	N = 319
	between		680.9993	0	2912.297	n = 29
	within		476.3687	-2008.296	3334.615	T = 11
Point of Sales (POS) Tax	overall	1294.164	2686.916	0	14984.63	N = 319
	between		2643.229	0	12635.72	n = 29
	within		672.7288	-1937.554	5044.553	T = 11
Income Tax	overall	59.73388	439.2034	0	4052.502	N = 319
	between		255.7836	0	1332.501	n = 29
	within		359.9052	-1272.767	2779.735	T = 11
Recurring Subsidies	overall	329.1998	619.6657	0	6202.211	N = 319
	between		446.2271	0	2123.141	n = 29
	within		437.1825	-373.6783	5775.533	T = 11
Charging Points Total	overall	3283.577	8246	0	66664	N = 319
	between		5636.925	19.63636	23072.91	n = 29
	within		6102.194	-19389.33	46874.67	T = 11
Fast Chargers	overall	346.8245	898.7076	0	7456	N = 319
	between		523.9059	0	1892.545	n = 29
	within		736.0906	-1545.721	5910.279	T = 11
Charging Points Total per 100km Highway	overall	159.5143	383.4443	0	3578.968	N = 319
	between		303.3466	2.149691	1539.145	n = 29
	within		240.6327	-844.0664	2199.337	T = 11
Fast Chargers per 100km Highway	overall	22.19925	78.9566	0	988.7189	N = 319
	between		50.96274	0	269.8418	n = 29
	within		60.98046	-247.4514	741.0764	T = 11
Electricity to Diesel Price	overall	0.0994366	0.0237409	0.0551923	0.1739604	N = 319
	between		0.0209028	0.0697496	0.1437885	n = 29
	within		0.0118509	0.0697496	0.1437885	T = 11
Trend	overall	7.608373	0.0015719	7.60589	7.610853	N = 319
	between		0	7.608373	7.608373	n = 29
	within		0.0015719	7.60589	7.610853	T = 11

Figure 8.2: EV Subsidies



The countries that offer in total the highest financial incentives for the purchase of an EV are Denmark and Norway. While the amount of subsidies for EVs have slightly decreased in Denmark over the last years, Norway exhibits the opposite development with an increasing amount of subsidies. A first indication of a positive relationship between subsidies and EV registration rate, which is illustrated in Figure 8.3, becomes evident when visually comparing the registration rate of countries that grant a substantial amount of monetary incentives with those that grant almost nothing.

Besides Denmark, a trend that can be noticed in several countries, when looking at the amount of the granted incentives is that they become smaller over the years and then rapidly increase again. This is because tax policies are very rarely reviewed and adjusted. When for example levying a tax that is based on CO_2 emissions, as it is for example the case in Greece, Germany or France, the difference of the taxable amount between ICCs and EVs decreases. The reason for the decrease in the price difference of the taxable amounts is based on the improvement in the CO_2 emissions of the ICC. While, BEVs are not able to improve their emission performance, as they already do not emit a single gram of CO_2 when they are operated, ICCs have gradually decreased the amount of CO_2 emissions. Thus, the slow adjustments of tax policies and the continuous improvement of the CO_2 emissions of ICCs do not help to make EVs more attractive from a financial perspective. To better illustrate this issue, the example of the circulation tax in Luxembourg can be discussed. The circulation tax in Luxembourg is determined on three components which are multiplied with each other. The first component is the CO_2 emissions of the vehicle, the second component is a factor that differs based on whether the vehicle is fueled with diesel or any other fuel and the last component is an additional factor the value of which depends on the CO_2 emissions of the vehicle. Thus, the lower the CO_2 emissions of a car, the smaller the last factor that is multiplied by the other two components of the tax. While reviewing the tax guides, it can be noticed that the threshold CO_2 emission values and the corresponding factors for the last component of the tax have not changed over the 11 year time period. Considering that the CO_2 emission of the VW Golf, which was used to represent the ICC, has decreased from 134g/km to 109g/km, the reduction in the circulation tax incentives over the last years can be explained. Such phenomenons cannot only be observed in Luxembourg but occur in different countries such as Germany, France or Greece as well.

Comparing the descriptive statistics presented in Table 8.1 to those reported in Chapter 7 the EV market, as hypothesised, has extensively developed since 2017, which is the final year of Münzel et al.'s 2019 investigation. For example the mean of the registration rate of EVs has more than doubled within the last three years of investigation. Having an even closer look at the registration rates of EVs, which are illustrated in Figure 8.3, it becomes evident that especially in the year 2020, the EV market has witnessed a strong growth. This could have several causes like the greater variety of available EV models, the decreasing prices for EVs or the more developed charging infrastructure. Thus the investigation of additional three years might not seem substantial for a mature and established product but it represents a considerable time for an innovative product in a quickly evolving market. Especially, when considering that EVs were introduced to the mainstream market around 2010 as most researchers agree on. Consequently, due to the advancements in the technology, the importance of subsidies could have significantly reduced since the investigation of Münzel et al. (2019). In the remainder of this chapter statistical analyses are carried out that can provide information whether this assumption is indeed correct.

As in the previous chapter, not one but in total nine models that differ based on the considered variables will be investigated throughout this chapter. These nine models can broadly be categorised into three regression groups that distinguish themselves from each other based on the way the charging infrastructure determinant is included. The first bunch of econometric models orientate on the work of Münzel et al. (2019) and include the determinants incentives, the ratio of the fuel prices and a trend variable. The second bunch of regression models incorporate the untransformed charging infrastructure determinant. The reason to include this determinant as a control variable into the regression is the significant Ramsey RESET test in the previous investigation. Thus, excluding the charging infrastructure may lead to a misspecification of the model. Lastly, all the models of the second bunch of regressions will also be analysed with a logarithmic transformation of the charging infrastructure determinant. Transforming this variable, however entails a significant downside. A transformation of this determinant into its natural logarithm will cause that 0 values become missing observations, as it is the case for the registration rate of EVs. Thus, important observations might not be considered in the investigation.

Within these groups, the models differ based on the level of detail with which

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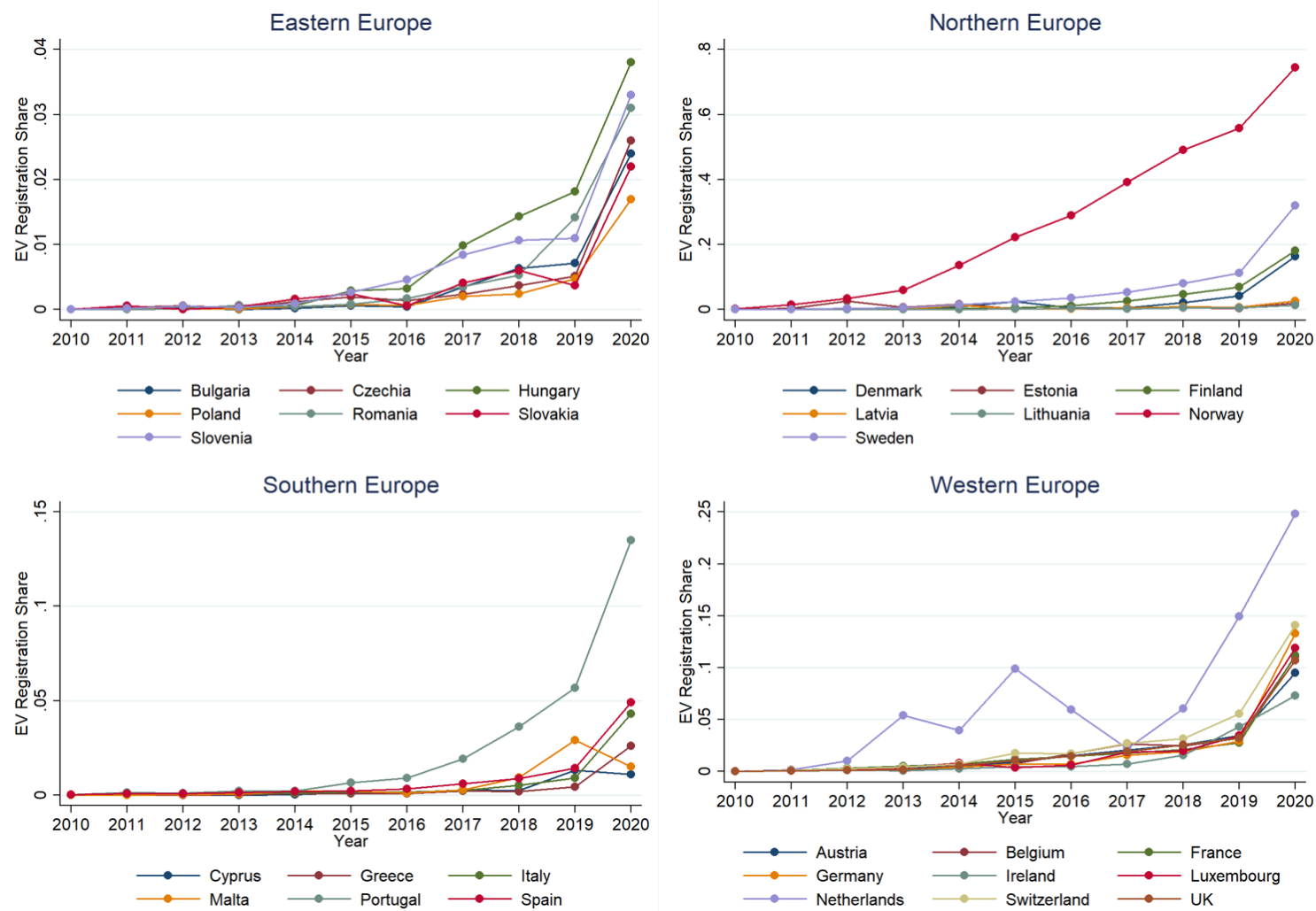
the financial incentive determinant is investigated. While the first model of each group exhibits the smallest level of detail for this factor by looking at an aggregated subsidies variable, the second model divides the monetary incentives into one time and recurring incentives. Lastly, the third model in each group exhibits the highest level of detail by further distinguishing between different types of one time subsidies.

Table 8.2: Considered Variables in the Models

Variable	Group 1			Group 2			Group 3		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Subsidies	✓			✓			✓		
One-Time Subsidies		✓			✓			✓	
Rebate			✓			✓			✓
VAT			✓			✓			✓
POSTax			✓			✓			✓
Income Tax			✓			✓			✓
Recurring Subsidies		✓	✓		✓	✓		✓	✓
Electricity to Diesel Price	✓	✓	✓	✓	✓	✓	✓	✓	✓
Trend	✓	✓	✓	✓	✓	✓	✓	✓	✓
Chargers per 100km highway				✓	✓	✓	✓	✓	✓

Note: The determinant *Chargers per 100km highway* is log transformed in the models of Group 3.

Figure 8.3: EV Registration Rate



8.1.2 Pooled OLS

The same data analysis structure as in the previous chapters is followed in this investigation. Therefore, the determinants are initially incorporated in a pooled OLS regression to obtain an initial idea of the influence and significances of the considered determinants. Running the regressions with robust standard errors to account for potential misspecifications yielded the following results reported in Table 8.3. The results indicate a generally highly significant and positive influence stemming from the amount of subsidies on the ratio of newly registered EVs. This conclusion can be derived from the coefficients of the variable *Subsidies* of the first regression of each group. When further breaking down subsidies based on whether they are granted once or frequently over time, the results of the regressions are somewhat mixed. While the influence of *One-Time Subsidies* on the EV market seems to be highly significant and positive regardless of the specification and group, the results for the variable *Recurring Subsidies* of the first two groups do not exhibit a significant influence on the EV registration rate. In contrast, this determinant is significant at a 10% level in the third group of regressions, where the charging infrastructure is considered and transformed into its natural logarithm. A potential explanation for the difference in significance could be the diminishing number of observations when applying an ln transformation to the charging infrastructure variable.

The results of the third alternative of the regression models, where the *One-Time Subsidies* variable is further broken down, all of the components are significant for the the first and second group. In the third group, only the coefficient of the variable *Income Tax* is insignificant and therefore deviates in this regard from the other two groups. Focusing on the control variables, no differences in the level of significance can be determined between the specifications and groups. The trend variable is highly significant in each specification, suggesting that the inclusion of such a determinant is important to account for unobserved time-varying variables. The variable that is supposed to account for the charging infrastructure in this regression also exhibits highly significant coefficients, in the regression where it is included in level but also in its natural logarithm form. A significant positive coefficient provides evidence for the assumed positive relationship between charging infrastructure and the registration rate of EVs. In addition, it is a first indication that the *Chargers per 100km highway* determinant is an important element of the regression model.

Table 8.3: Regression Results EV Market: Pooled OLS

Variable	Group 1			Group 2			Group 3		
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)
Subsidies	0.0189%*** (0.00002)			0.0136%*** (0.00002)			0.0097%*** (0.00002)		
One-Time Subsidies		0.0184%*** (0.00002)			0.0128%*** (0.00002)			0.0092%*** (0.00002)	
Rebate			0.0108%*** (0.00003)			0.0116%*** (0.00003)			0.0052%** (0.00002)
VAT			0.0510%*** (0.00010)			0.0297%*** (0.00007)			0.0324%*** (0.00006)
POSTax			0.0180%*** (0.00003)			0.0120%*** (0.00003)			0.0087%*** (0.00003)
Income Tax			0.0252%*** (0.00007)			0.0151%** (0.00007)			0.0097 (0.00008)
Recurring Subsidies		0.0269% (0.00017)	0.0276% (0.00018)		0.0242% (0.00015)	0.0237% (0.00015)		0.0170%* (0.00009)	0.0175%* (0.00010)
LN(Electricity to Diesel Price)	0.364% (0.34597)	0.352% (0.34484)	0.442% (0.33988)	0.413% (0.32228)	0.398% (0.32143)	0.427% (0.32783)	-0.085% (0.29303)	-0.093% (0.29304)	0.009% (0.29276)
Trend	1.2E+6%*** (47.858)	1.2E+6%*** (47.774)	1.2E+6%*** (45.652)	4.6E+5%*** (45.706)	4.6E+5%*** (45.620)	4.7E+5%*** (45.322)	2.3E+5%*** (48.926)	2.0E+5%*** (48.908)	2.2E+5%*** (48.407)
Chargers per 100km highway				0.1474%*** (0.00028)	0.1480%*** (0.00027)	0.1332%*** (0.00028)	0.4396%*** (0.04760)	0.4403%*** (0.04821)	0.4146%*** (0.04797)
Observations	296	296	296	296	296	296	249	249	249
F-score	192.16***	144.65***	95.03***	157.39***	127.35***	83.97***	127.62***	104.74***	79.88***
Overall R^2	0.6604	0.6610	0.6877	0.7233	0.7244	0.7284	0.7245	0.7253	0.7437

Note: The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$.

*** p < 0.1

** p < 0.05

* p < 0.01

Another observation that can be derived from the results is that the coefficients of the variables obtained from the different specifications from Group 1 and 2 are in general higher than those of the corresponding results for the third group. This can also potentially be traced back to the modification of the charging infrastructure variable and the missing observations. Moreover, the coefficients of the regressions that exclude the charging infrastructure determinant exhibit the highest values. This outcome, in conjunction with the high significance level of the charging infrastructure variable could indicate that the models with this specification suffer under omitted variable bias and thus over-report the influence of subsidies when applying a pooled OLS regression. A more thorough analysis of the results will, however, not take place at this stage as the purpose of these regressions was to obtain an initial idea of the influence of the determinants on the EV market. Moreover, it was supposed to provide initial guidance on which model should be applied. Considering the structure of the data set, regression models that are specifically developed to process a panel data set are more suitable. A pooled OLS might therefore not be the model that fits the data the best and could report biased estimates of the determinants. Consequently, the following section of this chapter is dedicated to find the model specification that is the most suitable to the data at hand and therefore to investigate the research hypotheses.

8.1.3 Model Specification

In the light of finding the model that fits the data the best, several diagnostic tests will be executed in the following. While the first tests aim to detect what particular panel data model should be applied, the tests carried out in the consecutive section deal with finding out whether the selected model complies with the Gauss-Markov OLS assumptions and measures that can be taken to counteract the drawbacks of potential violations. As the models within a group are quite similar, the results of the diagnostic tests usually do not deviate within these groups. Consequently, only the results and the implications they have on the model for the most detailed (third) model specification of each group will be discussed to avoid unnecessary repetition. The results of the other specifications are of course reported in the Appendix H and in cases where differences exist, they will be mentioned and discussed in the following subchapters.

8.1.3.1 Fixed Effects vs. Random Effects Model

Since the collected data consists of observations over time for multiple countries and thus is in form of a panel, the opportunity emerges to analyse the sample with panel regression models and benefit from the different advantages these regression models entail. Two of the standard panel data regression models are the FE and RE model. Before running such a panel data model, as in the previous chapters, first of all it should be ruled out that the poolability of the data provides better estimates for the determinants. To decide whether a panel data model should be applied, the results of an F-test and Breusch and Pagan (1979) LM test are consulted. Both the results of the F-test and Breusch and Pagan (1979) LM Test, favour the application of a panel data model. Significant F-scores as well as χ^2 values are not only obtained for the third specification of the groups, which are presented in Tables 8.4 and 8.5 respectively but also for all other specifications.

Table 8.4: F-Test

	Group 1	Group 2	Group 3
F	F(28, 260) = 16.73	F(28, 259) = 13.66	F(28, 212) = 8.45
Prob >F	0.0000	0.0000	0.0000

Table 8.5: Breusch and Pagan Lagrange Multiplier Test for Random Effects

	Group 1		Group 2		Group 3	
	Var	sd = sqrt(VAR)	Var	sd = sqrt(VAR)	Var	sd = sqrt(VAR)
EVReg	4.269434	2.066261	4.269434	2.066261	2.933794	1.712832
e	0.5398722	0.73476	0.5333234	0.7302899	0.4156921	0.6447419
u	0.7033085	0.8386349	0.4283573	0.6544901	0.4109864	0.6410822
	$\bar{\chi}^2(1)$	370.15	$\bar{\chi}^2(1)$	189.62	$\bar{\chi}^2(1)$	122.20
	Prob > $\bar{\chi}^2$	0.0000	Prob > $\bar{\chi}^2$	0.0000	Prob > $\bar{\chi}^2$	0.0000

Ruling out the application of a pooled OLS, the following diagnostic test should focus on answering the question whether the data is best fitted in an FE or RE model. The standard approach is to perform a Hausman (1978) Specification test to determine the correct model. Since the residuals of the regression model exhibit evidence of heteroskedasticity, Wooldridge (2010) advises to carry out an augmented regression instead of a Hausman test. Although, the application of an augmented regression is recommended, Hausman tests for all specification of all groups are also performed and reported in Appendix H.

Table 8.6: Mundlak Approach for FE vs. RE

	Group 1	Group 2	Group 3
χ^2	$\chi^2 (6) = 60.79$	$\chi^2 (7) = 141.70$	$\chi^2 (8) = 95.84$
Prob > χ^2	0.0000	0.0000	0.0000

The results of the augmented regression, presented in Table 8.6 are all highly significant and reject the joint null hypothesis that the differences in the coefficients are not systematic. Thus, the outcomes of the augmented regression correspond with those of the Hausman (1978) test and suggest the application of an FE model. Considering the selection of the control variables, this outcome is not surprising. In contrast to the model used in chapter 7, this model specification does not account for many time-invariant country differences that could potentially affect the EV market. Thus the omission of such determinants could lead to possible omitted variable bias when applying an RE model specification. In an FE model, the country dummy fixed effects terms or the within transformation of the variables control for these variables and thus can be omitted from the regression model. More importantly, however, in contrast to the variable *Innovativeness* of the previous chapter, the variable of interest in this investigation is not *sluggish* and exhibits sufficient within variation. Consequently, the loss in efficiency when applying an FE model should not have a too severe influence on the significance of the coefficients of this variable.

As an FE specification has been determined to be the most appropriate model specification, explicit econometric models for the nine alternatives can be defined as follows:

Regressions Group 1:

$$(8.1) \quad \ln(EV)_{it} = \beta_1 S_{it} + \beta_2 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_3 TR_{it} + \alpha_i + \epsilon_{it}$$

$$(8.2) \quad \ln(EV)_{it} = \beta_1 OS_{it} + \beta_2 RS_{it} + \beta_3 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_4 TR_{it} + \alpha_i + \epsilon_{it}$$

$$(8.3) \quad \begin{aligned} \ln(EV)_{it} = & \beta_1 R_{it} + \beta_2 VAT_{it} + \beta_3 PT_{it} + \beta_4 IT_{it} + \beta_5 RS_{it} \\ & + \beta_6 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_7 TR_{it} + \alpha_i + \epsilon_{it} \end{aligned}$$

Regressions Group 2:

$$(8.4) \quad \ln(EV)_{it} = \beta_1 S_{it} + \beta_2 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_3 TR_{it} + \beta_4 CP_{it} + \alpha_i + \epsilon_{it}$$

$$(8.5) \quad \ln(EV)_{it} = \beta_1 OS_{it} + \beta_2 RS_{it} + \beta_3 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_4 TR_{it} + \beta_5 CP_{it} + \alpha_i + \epsilon_{it}$$

$$(8.6) \quad \begin{aligned} \ln(EV)_{it} = & \beta_1 R_{it} + \beta_2 VAT_{it} + \beta_3 PT_{it} + \beta_4 IT_{it} + \beta_5 RS_{it} \\ & + \beta_6 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_7 TR_{it} + \beta_8 CP_{it} + \alpha_i + \epsilon_{it} \end{aligned}$$

Regressions Group 3:

$$(8.7) \quad \ln(EV)_{it} = \beta_1 S_{it} + \beta_2 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_3 TR_{it} + \beta_4 \ln(CP)_{it} + \alpha_i + \epsilon_{it}$$

$$(8.8) \quad \ln(EV)_{it} = \beta_1 OS_{it} + \beta_2 RS_{it} + \beta_3 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_4 TR_{it} + \beta_5 \ln(CP)_{it} + \alpha_i + \epsilon_{it}$$

$$(8.9) \quad \begin{aligned} \ln(EV)_{it} = & \beta_1 R_{it} + \beta_2 VAT_{it} + \beta_3 PT_{it} + \beta_4 IT_{it} + \beta_5 RS_{it} \\ & + \beta_6 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_7 TR_{it} + \beta_8 \ln(CP)_{it} + \alpha_i + \epsilon_{it} \end{aligned}$$

where the subscripts i and t denote the country and year, respectively. α_i denotes the country specific effects and ϵ_{it} the error term. The variable names for the abbreviation can be derived from Table 8.7.

Table 8.7: Variable Definition

Variable Abbreviation	Variable Name
S	Subsidies
OS	One-Time Subsidies
R	Rebate
VAT	VAT
PT	Point of Sales Tax
IT	Income Tax
RS	Recurring Subsidies
$\ln(\frac{EP}{DP})$	LN(Electricity to Diesel Price)
TR	Trend
CP	Chargers 100km highway

8.1.3.2 Gauss-Markov OLS Assumptions

After determining that an FE estimator provides the best data fit, the different Gauss-Markov OLS assumptions for the different models are tested in this section. The first test that is executed is a VIF test to rule out that the coefficient estimates are influenced by multicollinearity. The results for the models with the highest level of detail in regard to the break down of subsidies, presented in Table 8.8, show that no determinant exceeds the critical threshold VIF value of 10 or the more conservative threshold of 5. The highest VIF score for all different specifications is recorded for the $\ln$ transformed charging infrastructure determinant with 1.66. Hence, the presence of multicollinearity between the variables can be ruled out.

Table 8.8: VIF Test

Variable	Group 1		Group 2		Group 3	
	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
Rebate	1.14	0.875578	1.14	0.873871	1.21	0.828266
VAT	1.09	0.921649	1.27	0.784483	1.14	0.878950
Income Tax	1.04	0.960100	1.05	0.948846	1.08	0.924931
POSTax	1.12	0.892390	1.28	0.781489	1.39	0.718489
Recurring Subsidies	1.07	0.938440	1.07	0.935321	1.07	0.935407
LN(Electricity to Diesel Price)	1.05	0.948807	1.05	0.948751	1.09	0.914240
Trend	1.07	0.932857	1.19	0.843249	1.28	0.778313
Chargers per 100km highway			1.59	0.627643	1.66	0.601418
Mean VIF	1.08		1.21		1.24	

The next test is concerned with the specification of the models and also aims to control that they do not suffer from omitted variables. For this purpose a Ramsey RESET test including values of powers 2, 3 and 4 of the predicted dependent variable are carried out. The results in Table 8.9 indicate different results in

regard to potential misspecification of the models of the different groups. While a significant F-score for the models in the first group provides evidence that the model might be misspecified, the null hypothesis of a misspecification of the models in the third group can be rejected with p-values greater than 0.1. The results of the Ramsey RESET test for the second group of models can be interpreted in either direction. When using a threshold value of 0.05 for the significance level, the obtained result indicates no misspecification of the model. However, when applying a significance threshold level of 0.1, the null hypothesis of no misspecification can be rejected and the Ramsey RESET test provides evidence that the model is misspecified. In this investigation, the more widely accepted significance threshold level of 0.05 is used to determine whether the model is misspecified. Moreover, when looking at the Ramsey RESET test results of the other models in this group the probability of a misspecification decreases, determined based on the increase of the p-value of this test, with a reduction in complexity of the analysis of the subsidies variable. Based on the Ramsey RESET test it can be derived that the charging infrastructure variable is an important determinant for the model. Although, the results indicate the potential misspecification of the models from group 1, analyses are further executed with this specification to be able to compare the results obtained from these models with those in the study of Münzel et al. (2019).

Table 8.9: Ramsey RESET Test

	Group 1	Group 2	Group 3
F-score	F(3, 28) = 6.50	F(3, 28) = 2.76	F(3, 28) = 1.22
Prob >F	0.0018	0.0611	0.3195

To detect heteroskedasticity in the residuals of the models, visual analyses as well as a diagnostic test in form of a likelihood ratio test are executed. For the visual analysis the residuals of the regressions are plotted against the predicted values. All graphs illustrated in Figure 8.4, indicate the presence of slight heteroskedasticity. This assumption is supported with the test statistics of the likelihood ratio test. Significant χ^2 values for all specifications of all groups rule out the presence of homosekdasticity in the residuals.

Figure 8.4: EV Heteroskedasticity

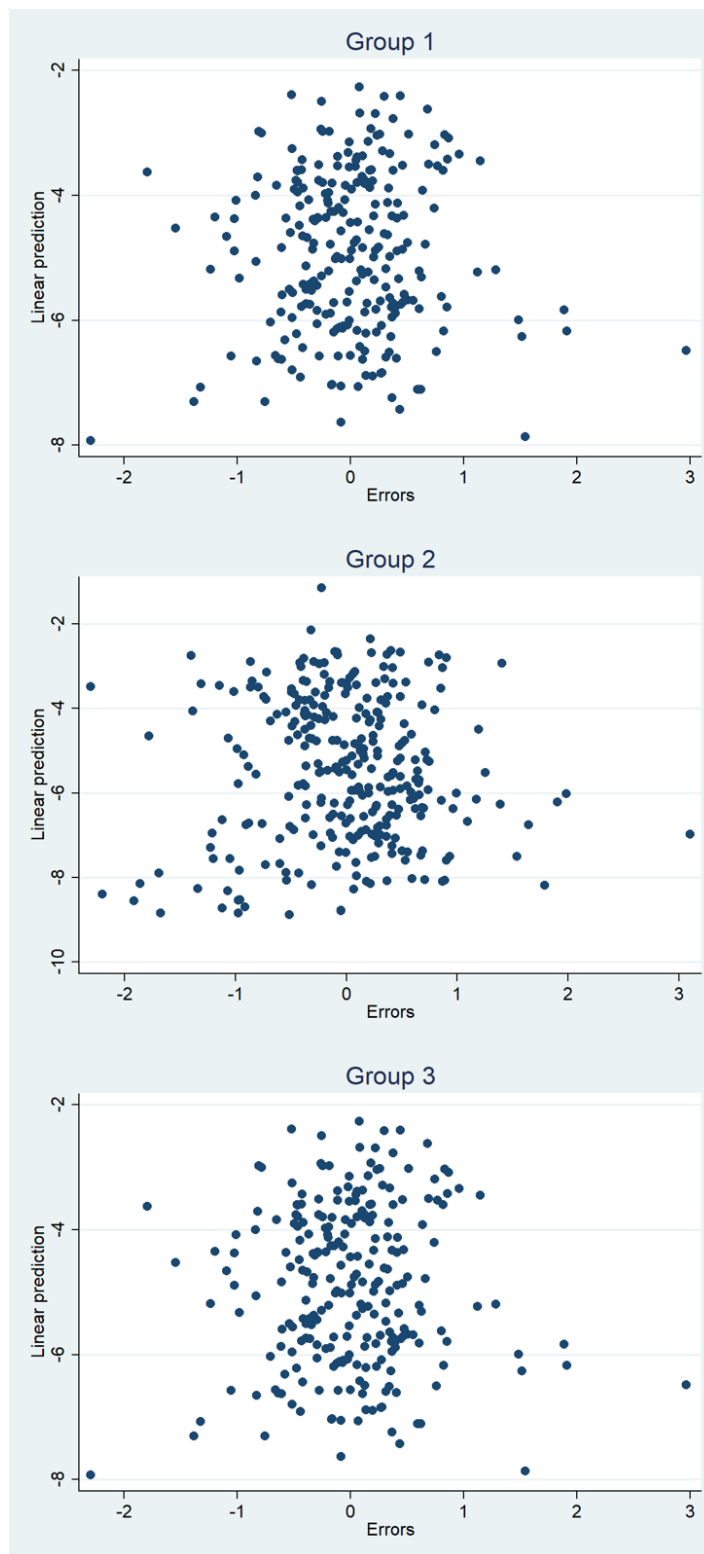


Table 8.10: Likelihood Ratio Test

	Group 1	Group 2	Group 3
χ^2	$\chi^2 (28) = 120.43$	$\chi^2 (28) = 101.51$	$\chi^2 (28) = 84.94$
Prob > χ^2	0.0000	0.0000	0.0000

Lastly, a Wooldridge test for autocorrelation is performed to test for a potential serial correlation of the residuals. The test results shown in Table 8.11 provide evidence for the existence of serial correlation.

Table 8.11: Wooldridge Test for Autocorrelation

	Group 1	Group 2	Group 3
F	F(1, 28) = 30.052	F(1, 28) = 30.299	F(1, 28) = 22.622
Prob > F	0.0000	0.0000	0.0001

Based on the results of the specification as well as diagnostic tests, the most suitable model for the data at hand is an FE model with SEs clustered at country level. The reason for clustering the SEs on country level is that according to Wooldridge (2010) this measure makes the SEs robust to potential influences of heteroskedasticity and serial correlation. In contrast to the previous investigation, the higher within variation of the main independent variable provides the advantage to be able to apply an FE model and therefore control for potential endogeneity problems.

8.1.4 Panel Regression

In this section, not only the estimates of the different specifications obtained from an FE specification are presented but also those calculated with a first difference approach, which is an often applied alternative to the FE approach. Since the sample is with 296 or 249 observations respectively, relatively small, it is assumed that the results of the FE models are more reliable. In addition, in this investigation it is believed that the most reliable results are obtained from the regressions in group 2. This assumption is made because on the one hand, in contrast to the regressions of group 1, the regressions did not exhibit a significant Ramsey RESET test and therefore seem not to be misspecified. On the other hand, in contrast to the regressions of group 3, the models of group 2 incorporate the charging infrastructure as a determinant but do not suffer from the loss of observations because of its ln transformation.

First of all, evaluating the model fit, all models exhibit a high explanatory power. The within R^2 value of each regression exceeds 80%, implying that the models are able to explain a lot of the residuals' variation. For the last regression of group 3, however, no F-score was able to be determined. This is because of losses in observations for the variable *Income Tax* due to the log transformation of the charging infrastructure variable. Since the model exhibits insufficient observations for this variable, the F-score for the entire model cannot be estimated any longer. This raises a general concern for the coefficients obtained in model specification 3 for all groups. Breaking down the variable subsidies too far could result in insufficient observations for the estimation of the coefficients so that the estimates might become unreliable.

Based on the results of the FE regressions reported in Table 8.12, it can be concluded that Subsidies significantly and positively influence the registration rate of EVs. Indifferent of the inclusion or ln transformation of the charging infrastructure determinant, the variable *Subsidies* exhibits a coefficient that is significant at a 1% level. Moreover, the marginal influence of this determinant is not strongly affected by the different specifications of the models which can be derived from the small differences of the coefficients between the groups. In particular, the model with the highest coefficient for this variable suggest an influence on the EV market that is only 0.0004% (0.0078% - 0.0074%) higher than the coefficient with the smallest value for *Subsidies*. Using the coefficient of the variable *Subsidies* from Model 8.4, an economic interpretation would be that assuming the EV registration rate formally would have been 1.0%, an increase in subsidies by 1,000 € would on average result in a registration rate of new EVs of 1.076% ($1\% \cdot (1 + (1000 \cdot 0.0076\%))$). Comparing this outcome with the estimate Münzel et al. (2019) obtained for the influence of Subsidies, the coefficients are slightly higher. This could have several reasons, from differences in the calculation of subsidies to the exclusion of the countries Croatia and Iceland to the extension of the analysis by 3 years until 2020.

Breaking down the *Subsidies* variable into one time subsidies and recurring subsidies, mixed results are obtained. While the coefficients of the variable *One-Time Subsidies* are significant at a 5% level independent of the inclusion of the charging infrastructure variable, *Recurring Subsidies* are only significant for the regressions of groups 1 and 2. A potential explanation for the insignificance of the recurring subsidies in the third group of regressions could be the fewer number of observations when applying an ln transformation to the charging infrastructure

determinant. Comparing the magnitude of the coefficients of the one time and recurring subsidies, it can be seen that while the coefficients of both are positive, recurring incentives exercise an impact on the registration rate of EVs that is much higher than that of one-time subsidies.

In the last specification of the regression models, the results of the groups 1 and 3 suggest that rebates are the only one time subsidy that significantly positively influence the sales of EVs. In addition to this variable the point of sales subsidies also exhibit a significant influence on the EV market. This coefficient is however, only significant at a 10% level. The magnitude of the influence of *Rebates* on the EV registration rate is with a range of 0.0068% to 0.0073%, as almost all determinants considered in the regression models, relatively similar between the groups.

Focusing on the control variables, the trend variable proves its importance for the regressions with coefficients that are significant at a 1% level. The value of the coefficients themselves do not provide any additional insights since the main purpose of this variable is to capture general trends in this market. Therefore, the coefficients will not be interpreted in the discussion of the results. The other two control variables exhibit mixed results depending on the group of regressions. While for example the ratio of the electricity to diesel price is significant at a 10% level for the first two groups, this determinant becomes insignificant in the last group of regressions. The negative signs of the coefficients are however as expected and imply that when the electricity price increases and the diesel price remains the same, this would have a negative influence on the registration rate of new EVs. The reason for this negative relationship is that an increasing ratio of these fuel prices would mean higher operating costs of EVs. Mixed results are also obtained for the determinant *Chargers per 100km highway*. Employing an ln transformation of this variable causes this variable to turn from highly significant to insignificant. Furthermore, the same peculiarity as observed in the previous chapters can be noticed for the charging infrastructure determinant in the second group of regressions. Based on the regression results, the conclusion could be made that an improvement in charging infrastructure would cause a reduction in the sales of EVs.

Moving on with the analysis, the results of the regressions that are obtained with a first difference approach can be seen in Table 8.13. As previously mentioned since a higher validity of the results obtained from an FE specification is expected, only a brief description of the results with the FD approach takes

place at this stage. In particular, the description is mostly limited to presenting outcomes that strongly diverge from those of the FE models. The results of the FD estimates are mostly in line with those of the FE models. The coefficients for the variables *Subsidies*, *One-Time Subsidies* and *Rebate* are slightly higher than those of their counterparts estimated with the FE specification but do not strongly differ in the significance level. Noticeable is however, that the coefficient of the variable *VAT*, which is insignificant with the FE specification, is significant at a 1% level throughout all groups. Furthermore, while the variable *VAT* has gained in significance, the determinant *Recurring Subsidies* has lost all its significance in the third specification of all groups. Another interesting observation is that the *POSTax* becomes significant at a 5% level and exhibits a negative influence on the EV market. This outcome is counter intuitive as a negative influence would imply that higher subsidies would discourage people to purchase EVs.

A discussion of the results, in the context of previous research, will take place after their robustness has been tested in the following section and analyses for the individual BEV and PHEV types are performed. At this stage potential implications for politics will be discussed.

Table 8.12: Regression Results EV Market: Fixed Effects Models

Variable	Group 1			Group 2			Group 3		
	Model 8.1	Model 8.2	Model 8.3	Model 8.4	Model 8.5	Model 8.6	Model 8.7	Model 8.8	Model 8.9
Subsidies	0.0074%*** (0.00003)			0.0076%*** (0.00002)			0.0078%*** (0.00002)		
One-Time Subsidies		0.0063%** (0.00003)			0.0066%** (0.00003)			0.0066%** (0.00002)	
Rebate			0.0073%** (0.00003)			0.0068%** (0.00003)			0.0072%*** (0.00002)
VAT			0.0028% (0.00010)			0.0015% (0.00009)			0.0127% (0.00009)
POSTax			0.0034% (0.00007)			0.0082%* (0.00005)			0.0008% (0.00003)
Income Tax			-0.0073% (0.00008)			-0.0044% (0.00007)			0.0019% (0.00006)
Recurring Subsidies		0.0242%* (0.00012)	0.0251%* (0.00013)		0.0225%** (0.00011)	0.0242%** (0.00012)		0.0225% (0.00016)	0.0213% (0.00015)
LN(Electricity to Diesel Price)	-0.984%* (0.57079)	-1.061%* (0.57034)	-1.067%* (0.58134)	-1.069%* (0.57596)	-1.132%* (0.57351)	-1.166%* (0.58716)	-0.648% (0.55122)	-0.726% (0.56233)	-0.727% (0.58505)
Trend	4.5E+6%*** (46.295)	4.5E+6%*** (47.640)	4.7E+6%*** (49.610)	7.1E+6%*** (54.781)	6.9E+6%*** (56.341)	7.3E+6%*** (60.798)	6.0E+5%*** (106.10)	6.1E+5%*** (105.53)	5.3E+5%*** (115.98)
Chargers per 100km highway				-0.0486%*** (0.00011)	-0.0456%*** (0.00012)	-0.0455%*** (0.00015)	0.0716% (0.09073)	0.0737% (0.09087)	0.0847% (0.10253)
Observations	296	296	296	296	296	296	249	249	249
F-score	291.14***	219.51***	129.83***	264.13***	260.12***	162.72***	218.55***	209.94***	n.a.
Within R^2	0.8459	0.8478	0.8489	0.8492	0.8506	0.8513	0.8069	0.8097	0.8110
Between R^2	0.0001	0.0001	0.0149	0.0777	0.0649	0.0586	0.0731	0.0649	0.0277
Overall R^2	0.6031	0.6021	0.5793	0.5455	0.5487	0.5448	0.5552	0.5535	0.5332

Note: Country Fixed Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** p < 0.01

** p < 0.05

* p < 0.1

Table 8.13: Regression Results EV Market: First Differences Models

Variable	Munzel			Charger			log charger		
	Model 8.1	Model 8.2	Model 8.3	Model 8.4	Model 8.5	Model 8.6	Model 8.7	Model 8.8	Model 8.9
Subsidies	0.0085%*** (0.00002)			0.0085%*** (0.00002)			0.0082%*** (0.00003)		
One-Time Subsidies		0.0080%*** (0.00003)			0.0079%*** (0.00003)			0.0074%** (0.00003)	
Rebate			0.0090%** (0.00003)			0.0089%** (0.00003)			0.0091%** (0.00004)
VAT			0.0134%*** (0.00003)			0.0138%*** (0.00002)			0.0165%*** (0.00003)
POSTax			-0.0089% (0.00007)			-0.0097% (0.00006)			-0.0151%** (0.00007)
Income Tax			0.0164% (0.00021)			0.0188% (0.00020)			0.0059% (0.00004)
Recurring Subsidies		0.0121%* (0.00007)	0.0122% (0.00007)		0.0120%* (0.00007)	0.0121% (0.00007)		0.0125% (0.00008)	0.0129% (0.00008)
LN(Electricity to Diesel Price)	-1.333%*** (0.46902)	-1.355%*** (0.47666)	-1.306%*** (0.49869)	-1.335%*** (0.47195)	-1.356%*** (0.47904)	-1.302%** (0.49945)	-0.660% (0.52927)	-0.680% (0.52737)	-0.619% (0.54353)
Trend	3.0E+7%*** (61.357)	3.0E+7%*** (61.929)	2.6E+7%*** (62.588)	4.8E+7%*** (76.703)	4.9E+7%*** (77.287)	4.5E+7%*** (77.902)	2.4E+6%*** (85.265)	2.6E+6%*** (87.846)	2.0E+6%*** (89.219)
Chargers per 100km				-0.0512%** (0.00024)	-0.0511%** (0.00024)	-0.0591%** (0.00023)	0.0007% (0.09268)	-0.0072% (0.09271)	-0.0081% (0.09364)
Observations	266	266	266	266	266	266	220	220	220
F-score	263.58***	206.83***	332.15***	225.90***	186.13***	2258.07***	150.54***	124.23***	n.a.
Overall R^2	0.4386	0.4391	0.4457	0.4410	0.4415	0.4488	0.3924	0.3938	0.4125

Note: First Difference model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** p < 0.01
 ** p < 0.05
 * p < 0.1

8.1.5 Robustness Tests

To check the validity of the results, different robustness tests are performed in the following. In particular, in one robustness test the trend variable is replaced by time dummy variables, which creates a country-time fixed effects model. In the second robustness test a different statistical approach in form of dynamic panel data models is applied to control for the adequacy of the results. Lastly, a change in the magnitude of the influence of subsidies on the EV market is analysed by limiting the time frame to 2017.

8.1.5.1 Time Dummies

In the first robustness test, time dummy variables replace the trend variable in the regression. Thus, by adding time dummies in the models, a two-way fixed effects model is established. The advantage of such a model is that by including time dummy variables, it can be accounted for time based shocks in the analysis. This comes however at the cost of losses in the degrees of freedom of the model due to the inclusion of 10 additional variables in the analysis.

Running the regressions with the time dummies yielded the results depicted in Table 8.14. First of all, when looking at the significance of the coefficients, the variable *Subsidies* is still highly significant and positive, supporting the findings from the main part of the investigation. Moreover, the obtained estimate in this robustness test is almost equal to the coefficient reported in the previous section, providing evidence that the magnitude of the influence of subsidies on the EV market is correctly approximated. Focusing on the estimates for the different subsidies variables that are based on whether they are granted once or more frequently, it can be seen that while the variable *One-Time Subsidies* has gained in significance in comparison to the results of the main analysis, the determinant *Recurring Subsidies* exhibits estimates that are not significant at all anymore. The results for the latter variable, therefore amplify the previously expressed doubts regarding the influence of this determinant. On the contrary the highly significant estimates for the *One-Time Subsidies* as well as the individual one time subsidy *Rebate* variables confirm the outcomes of the previous analysis. Another difference between the results presented in Table 8.14 and 8.12 can be identified for the variable *POSTax* in the second group of regressions. While this variable was significant at a 10% level in the main part of the investigation, it turns out to be

insignificant when including time dummy variables into the regression. Considering the previously mentioned lack of observations for some of the individual one-time subsidies variables, it cannot clearly be determined whether these variables exhibit a significant influence.

A conclusion that can be derived from the significance as well as the magnitude of the estimates of the time dummies, is that the application of a trend variable in the main part of the investigation is appropriate. The estimates of all time dummies are highly significant and increase in magnitude as the years proceed. The steady growth of the time dummy coefficients can be interpreted as a trend in the market. Hence, the same behavior can be expected to be captured by a trend variable (Münzel et al., 2019). Thus, based on the results obtained in this part of the investigation, it can be concluded that the regression results of the main part of the investigation are robust.

Table 8.14: Regression Results EV Market: Fixed Effects with Time Dummies

Variable	Group 1			Group 2			Group 3		
	Model 8.1	Model 8.2	Model 8.3	Model 8.4	Model 8.5	Model 8.6	Model 8.7	Model 8.8	Model 8.9
Subsidies	0.0077%*** (0.00002)			0.0078%*** (0.00002)			0.0074%*** (0.00002)		
One-Time Subsidies		0.0071%*** (0.00002)			0.0072%*** (0.00002)			0.0068%*** (0.00002)	
Rebate			0.0083%*** (0.00003)			0.0076%*** (0.00003)			0.0075%*** (0.00003)
VAT			0.0042% (0.00009)			0.0026% (0.00008)			0.0143% (0.00010)
POSTax			0.0027% (0.00007)			0.0077% (0.00005)			0.0005% (0.00004)
Income Tax			0.0027% (0.00008)			0.0053% (0.00007)			0.0053% (0.00006)
Recurring Subsidies		0.0178% (0.00011)	0.0179% (0.00011)		0.0158% (0.00010)	0.0167% (0.00010)		0.0153% (0.00013)	0.0138% (0.00012)
LN(Electricity to Diesel Price)	-0.4008% (0.64011)	-0.4341% (0.64334)	-0.4139% (0.64403)	-0.5207% (0.61037)	-0.5429% (0.61444)	-0.5564% (0.60950)	-0.3209% (0.58991)	-0.3535% (0.59079)	-0.3389% (0.57544)
Chargers per 100km highway				-0.0472%*** (0.00011)	-0.0454%*** (0.00012)	-0.0456%*** (0.00014)	0.0808% (0.10041)	0.0826% (0.10009)	0.0911% (0.11407)
Time Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	296	296	296	296	296	296	249	249	249
F-score	133.22***	133.06***	208.27***	200.67***	194.94***	427.38***	257.83***	253.27***	n.a.
Within R^2	0.8918	0.8924	0.8930	0.8947	0.8952	0.8953	0.8476	0.8483	0.8498
Between R^2	0.0022	0.0020	0.0570	0.1243	0.1153	0.1280	0.0599	0.0590	0.0142
Overall R^2	0.6339	0.6341	0.6055	0.5762	0.5787	0.5724	0.5708	0.5713	0.5453

Note: Country Fixed Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** p < 0.01

** p < 0.05

* p < 0.1

8.1.5.2 Dynamic Regression Models

As determined in the model specification, the residuals of the different models suffer from serial correlation and thus provide evidence that the models might not account for all different time-invariant factors that exhibit an influence on the EV market. Moreover, Jenn et al. (2013) claim that standard FE approaches as applied in the main part of the investigation cannot consider the positive network externalities of such an innovation as they do not allow the inclusion of a lagged dependent variable. According to the researchers, ignoring to account for the natural growth of this vehicle type would result in positively biased estimates. However, to account for these issues a trend variable has been included in the regression models as well as robust standard errors clustered at country level have been applied to specifically counteract the biases arising from serial correlation that could influence the SE estimates. Also, when looking at the registration rate of the vehicles, apart from the last year, no severe sudden increase can be identified. Nevertheless, to account for this potential issue that could have distorted the coefficient estimates, a lagged dependent variable is added to the regression as another robustness test in this part of the investigation. A result of the inclusion of a lagged dependent variable is however an immediate endogeneity problem when trying to perform an OLS (Roodman, 2009), wherefore the application of dynamic panel data models is required. Consequently, two different approaches are considered in the following that are able to process a lag of the dependent variable and are developed to cope with possible endogeneity issues. These approaches are a GMM approach as well as a bias corrected Least-Squares Dummy Variables (LSDVC) dynamic panel data estimator.

Starting with the GMM approach, a difference GMM following the approach of Arellano and Bond (1991) is applied. The decision to perform a difference GMM instead of a system GMM can be based on two rules of thumb introduced by Blundell and Bond (1998) and Bond et al. (2001). Both rules are concerned with the coefficient value of the lagged dependent variable. In the first rule of thumb the estimate for the lagged dependent variable, which has been defined as α in Equation 5.38, is checked regarding whether it suggests that the autoregressive process becomes too persistent and close to being a random walk. In particular, it is recommended to use a system GMM in case α approaches the value 1. The second rule of thumb is more practical oriented. For this purpose estimates for the lagged dependent variable should be obtained in an OLS as well as FE model

setting. These coefficients of this variable then represent an upper (OLS) and lower bound (FE) respectively. In a consecutive step, the estimate for the lagged dependent variable should be calculated with a difference GMM approach. In case the estimate of the lagged dependent variable of the difference GMM model is close or below the lower bound, the results would indicate that weak instrumentation downward biases this estimate and the application of a system GMM is suggested. In this investigation, the estimates that are obtained (see Table 8.15) are however well positioned between the upper and lower bounds and therefore support the use of a difference GMM. The decision to carry out a difference GMM is also in line with previous research in this field (Jenn et al., 2013).

A GMM model can be considered appropriate if no second order autocorrelation can be detected in the residuals as well as if it does not exhibit signs of over-identification. To determine that this is the case an insignificant AR(2) as well as Hansen (1982) test should be obtained for the model. The interpretation of the Hansen test should however be made more cautiously and an insignificant test result not accepted without further consideration. Roodman (2009) points out that a Hansen test reporting a high p-value such as 0.25 or larger could be too good to be true and therefore can be interpreted as a potential problem in the model. Since the application of a GMM model requires different specifications in terms of for example the lag length of the dependent variable, Roodman (2009) suggest to carry out several models and explain how these differentiate themselves from each other and what influence they have on the two test statistics. Following this recommendation, GMM models with different specifications were executed. Nevertheless, only the results of the models of each group providing the best scores for the test statistic are reported in this section.²

The specification of the final model is in form of a two-step GMM to account for heteroskedasticity and serial correlation in the residuals. Moreover, a Windmeijer (2005) finite sample correction is applied to account for the relatively small sample size and orthogonal deviations are applied for potential gaps in the panels. Lastly, taking advantage of the collapse option of the statistical code developed by Roodman (2009) limits the proliferation of the instruments, so that the number of instruments remains below the number of groups considered in the analysis. Since the data set is relatively small, the GMM approach is only applied to the models with the aggregated *Subsidies* variable. Incorporating too many variables would result in a

²The results for other GMM model specifications can be found in Appendix I

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relatively large amount of instruments which would lead to an over-identification of the models. Furthermore, the trend variable from the main analysis is as suggested by Roodman (2009) replaced with time dummies to remove potential shocks from the errors that have affected the EV market in all countries.

Table 8.15: Results EV Market: Difference GMM

Variable	Group 1	Group 2	Group 3
L.ln(EV registration share)	0.5241%** (0.23125)	0.4495%*** (0.15206)	0.4862%* (0.25798)
Subsidies	0.0059%** (0.00003)	0.0058%*** (0.00002)	0.0055%* (0.00003)
LN(Electricity to Diesel Price)	-0.4449% (0.76772)	-0.2446% (0.56694)	-0.4169% (0.85737)
Chargers per 100km		-0.0463%*** (0.00007)	-0.0057% (0.07265)
Yearly Time-Dummies	✓	✓	✓
Two-step GMM	✓	✓	✓
Robust	✓	✓	✓
Windmeyer correction	✓	✓	✓
Orthogonal	✓	✓	✓
Observations	237	237	217
F-score	535.07***	398.68***	461.49***
Number of Instruments	20	21	21
Instruments (lags used)	EV (1)	EV (1)	EV (1)
AR(2) probability	0.835	0.900	0.914
Hansen J statistic	0.111	0.095	0.085
FE Lower Bound	0.33004	0.31970	0.32034
OLS Upper Bound	0.77604	0.74260	0.70853

The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** p < 0.01

** p < 0.05

* p < 0.1

First, evaluating the suitability of the model specifications, the diagnostic tests, reported in Table 8.15 should be analysed. Only the model of Group 1 provides evidence for a correct specification. While the test for second order correlation rules out the presence of such for the models of all groups, the Hansen test is only for the model of Group 1 clearly insignificant by simultaneously not exhibiting a too large p-value. Thus, only the model of the first group is most certainly not over-specified. Looking at the Hansen test of the other two models, the Hansen J statistics turns out to be significant at a 10% but not at a 5% level. Increasing the lag length of the dependent variable also only results in a deterioration (higher probability to reject Null hypothesis) of the Hansen J statistics. Since the Hansen J statistics are failed to be rejected at a 5% level and the applied specification as well as lag length leads only to a deterioration of the test statistics, it is assumed that the reported results are nevertheless the most valid for these groups.

Focusing now on the main independent variable *Subsidies*, the test results suggest that this determinant also exhibits a significant influence on the EV market

in this setting, supporting the results obtained from the baseline analysis. While the magnitude of the estimates is quite similar across the models of the groups, the variable exhibits different levels of significance depending on the inclusion of the charging infrastructure determinant. While the highest level of significance is obtained with the inclusion of an untransformed charging infrastructure, the variable *Subsidies* is only significant at a 10% level in the model of Group 3. A potential explanation for this change in significance could be the loss in observations due to the ln transformation of the dependent variable. Comparing the results of the difference GMM model with those obtained from the FE regressions of the main analysis as well as those of the robustness tests including time dummies, the estimates for the main independent variable are substantially smaller in this part of the investigation. For example, the difference between the coefficient of *Subsidies* of the regression in Group 2 between the FE regression in the main part of the analysis and the GMM approach applied in this section is 0.0018% (0.0076% - 0.0058%). Thus, an increase of 1,000 € in subsidies equals a deviation of almost 2% in the predicted influences on the EV market. This is a considerable amount when considering that the difference between those values is almost a third of the estimated influence based on the coefficient approximated with the GMM approach. Consequently, the results provide evidence and support for the requirement to account for the natural growth of an innovative product expressed by Jenn et al. (2013).

In light of a relatively small amount of data points, a GMM might not be the best dynamic panel data approach as the estimates could suffer from small-sample bias because of weak instruments. An alternative to a GMM approach that is able to deal with a lagged dependent variable and provides good estimates for a small sample is the LSDVC model. Thus, this dynamic panel data model specification with an Arellano and Bond (1991) bias correction is run as a second robustness test in this part of the investigation. Furthermore, the variance-covariance matrix is calculated based on a bootstrap resampling approach with 100 repetitions.

The results presented in Table 8.16 confirm once again the significance of the *Subsidies* determinant in explaining changes in the registration rate of EVs. Focusing on the estimated magnitude of the influence of this determinant, the coefficient values are situated between the estimates obtained from the FE approach and the GMM approach. Thus, derived from the results of the regressions it can be concluded that the FE estimator does not too strongly over-report the influence

of *Subsidies* as suggested by the estimates of the GMM analysis. Nevertheless, according to the results a slight overestimation of approximately 1% per 1,000€ subsidies of the FE estimates can still be identified.

Table 8.16: Results EV Market: LSDVC Models

Variable	Group 1	Group 2	Group 3
L.ln(EV registration share)	0.4481%*** (0.06618)	0.4221%*** (0.06643)	0.4478%*** (0.06426)
Subsidies	0.0065%*** (0.00002)	0.0066%*** (0.00002)	0.0057%*** (0.00002)
LN(Electricity to Diesel Price)	-0.3619% (0.41661)	-0.4598% (0.42045)	-0.5184% (0.47419)
Chargers per 100km		-0.0434%** (0.00018)	0.0589% (0.05068)
Yearly Time-Dummies	✓	✓	✓
Bias correction	AB estimator	AB estimator	AB estimator
Bootstrap number	100	100	100

The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. AB stands for Arellano and Bond (1991).

*** p < 0.01

** p < 0.05

* p < 0.1

8.1.5.3 Limited Time Frame

In this robustness test, it is analysed whether the influence of subsidies has as hypothesised in the literature review actually decreased over the last years. For this purpose, the investigated time frame of the analysis has been reduced and only captures the years 2010 to 2017. The considered regression models for this robustness test are all from Group 1 and thus exclude the charging infrastructure as a determinant. The decision to omit the charging infrastructure determinant is to save degrees of freedom which becomes more important due to the smaller sample size as a result of reducing the investigated time period. Moreover, the estimates from the main part of the analysis were quite similar across the groups, suggesting a minor difference for the main independent variable whether this factor is included or not. Also, the results for the model with the most detailed level of subsidies is not reported, as with the larger data set issues in terms of too few observations already arose. However, in addition to the FE models, the LSDVC approach with the same specifications determined in the previous sub-chapter is applied to the aggregated subsidies alternative.

The results of the different regressions are reported in Table 8.17 and exhibit a significant and positive influence of subsidies on the registration rate for all model alternatives. The significance of the *Recurring Subsidies* variables has even improved and is significant at a 5% level. Consequently, the first conclusion that

can be derived from the results is that they support the findings of the main part of the analysis. To evaluate whether the effect size of the influence has as assumed decreased, the magnitude of the coefficients from this investigation have to be compared to those of the main part of the analysis. In general, the estimates obtained for the regressions that was limited until the year 2017 exhibit higher values than those covering the entire time period. The greatest difference can be identified for the *Subsidies* determinants approximated with the LSDVC approach. A difference of 0.0026% can be considered substantial, therefore confirming the the hypothesis that the influence of subsidies has decreased. The estimates for the disaggregated *One-Time subsidies* variable does not differ as strongly as the aggregated subsidies variables in magnitude when reducing the time frame. In contrast to the *One-Time subsidies*, there is a 0.027% difference in the estimates between the recurring subsidies determinant, suggesting that the difference in the aggregated subsidies variable might be driven by the recurring subsidies.

Table 8.17: Results EV Market: Time Frame 2010-2017

Variable	LSDVC	Model 8.1	Model 8.2
L.ln(EV registration share)	0.3518%*** (0.08065)		
Subsidies	0.0091%*** (0.00003)	0.0084%** (0.00003)	
One-Time Subsidies			0.0067%** (0.00003)
Recurring Subsidies			0.0278%** (0.00015)
LN(Electricity to Diesel Price)	-1.2090%* (0.71208)	-2.5637%*** (0.69834)	-2.6717%*** (0.70307)
Trend		2.4E+7%*** (63.7346)	2.5E+7%*** (65.7432)
Yearly Time-Dummies	✓		
Bias correction	AB estimator		
Bootstrap number	100		
Observations		209	209
F-score		171.95	122.62
Within R^2		0.7810	0.7843
Between R^2		0.0001	0.0006
Overall R^2		0.3956	0.3895

The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. AB stands for Arellano and Bond (1991).

*** $p < 0.01$

** $p < 0.05$

* $p < 0.1$

8.2 Battery Electric Vehicle

While the previous investigation has focused on determining the influence of subsidies on the general EV market, thus merging the BEV and PHEV registration rate, this part of the study is concerned with analysing the influence of this determinant on the BEV market. Breaking down the EV market, into its different vehicle types may provide important insights as to how a subsidy could influence the sales of the particular vehicle type. This is especially important since BEVs are the only solution for the turn around to a completely CO_2 neutral transportation sector. In addition, there are several cases where BEVs are granted different subsidies than PHEVs. Thus, dedicating a section of the chapter to analysing the influence of subsidies on the BEV registration rate could help understanding whether there are differences in the effectiveness of subsidies. The analysis in this section is conducted in the same manner as in the previous subchapter.

8.2.1 Descriptive Statistics

This investigation also starts with a discussion of the amount of BEV subsidies identified in the 29 countries over the considered time period. For this purpose, Figure 8.5 has been developed, which employs the unprocessed data and depicts the amount of subsidies for the countries in the respective years.

For the aggregated (one-time and recurring) *Subsidies* variable, the amount of intended incentives falls below 0 in only five observations in the sample. While the negative incentives identified in Poland were also observed in the previous subchapter, where the subsidies for the merged EV market was discussed, Spain in contrast did not previously exhibited negative values for the Variable *Subsidies* at any point in time. First of all, when analysing the cause for the negative amount of subsidies and breaking it down into its individual components, the reason for the negative value lies in the *Recurring Subsidies* component. Diving deeper into the data set and the data estimation process, the particular reason for the negative subsidy amount could be identified as the levied company car tax by the state. When looking at the calculation of the tax it can be seen that the previously described drawbacks of the calculations which consider different car attributes also apply to this case. The taxes for the private use of a company car is usually based on a percentage that is levied on either the list price of a car or the total cost of acquisition. In Spain a reduction of 30% of the payment in kind value is granted

for company cars that are driven by electricity. A 15% reduction is however also granted to company cars that have CO_2 emissions below 120g/km, a requirement which is met by the considered ICC. Thus, the obtained payment in kind advantage of driving a BEV as a company car reduces to a 15% reduction in the payment in kind. This is however, not a sufficient reduction to compensate the price difference between BEVs and ICCs. Consequently, since the calculation of the tax is based on the vehicle price, the government must increase the granted payment in kind reduction to overcome the price gap between ICCs and BEVs so that the subsidy poses an actual incentive to shift from the purchase of an ICC to a BEV. The question that arises is why is the variable *Subsides* in Spain negative only now and not in the EV case? The explanation for this occurrence is that the total amount of subsidies for PHEVs must be greater in absolute terms than the negative value calculated for BEVs. Thus, since the EV subsidies were calculated as an average of the BEV and PHEV subsidies, the PHEV subsidies have out-weight the BEV subsidies. Consequently, this example provides support for the analysis in the way that subsidies might differ based on vehicle type and therefore a standalone investigation of each vehicle type makes sense.

Other noticeable examples of subsidies on a more detailed level that are negative are the point of sales taxes in France in the years 2019 and 2020 or the company car taxes in the Netherlands in 2010 and 2011, which are again caused by the same problems as pointed out earlier.

Figure 8.5: BEV Subsidies with Negative Amounts



Note: Structure of the illustration is based on Münzel et al. (2019). Focus of this graphic should be on the negative amount of subsidies. Since a continuous scale is used to present the amount of subsidies in the graphics, amounts that are close to 0 might also be illustrated in white. Therefore, it is recommended to also refer to the graphic that depicts the amount of subsidies where negative values have been eliminated to obtain a clearer picture of the amount of subsidies.

8.2. BATTERY ELECTRIC VEHICLE

For the main analysis, all negative subsidies have also been eliminated in this part of the investigation. To obtain more insights about the final subsidies as well as the dependent variable, descriptive statistics are executed and reported in Table 8.18. It should be noted that only the dependent and main independent variables differ from the descriptive statistics presented in Table 8.1.

Table 8.18: Descriptive Statistics: BEV Market

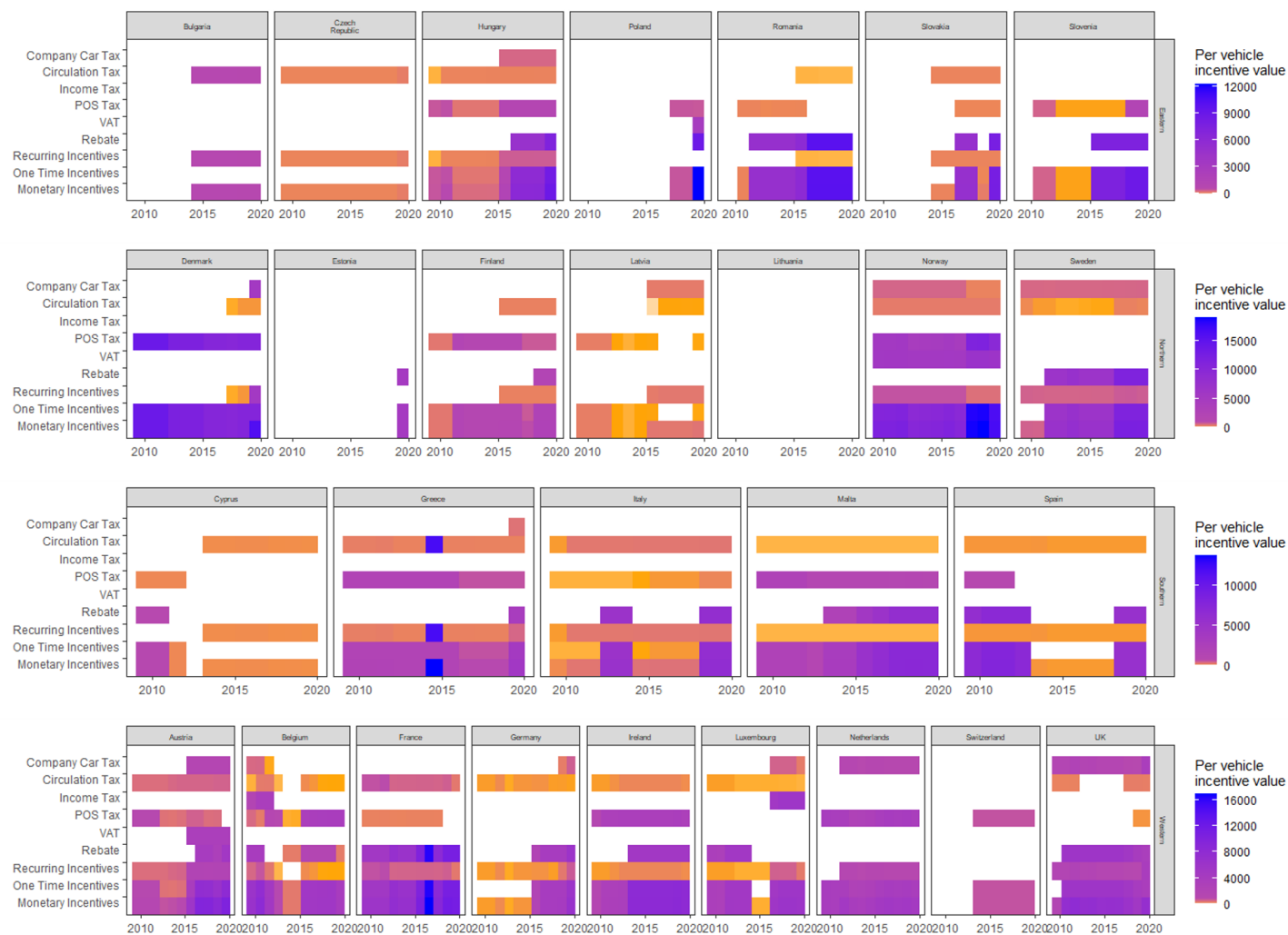
Variable		Mean	Std. Dev.	Min	Max	Observations
BEV Registration Share	overall	0.0142401	0.0477894	0	0.516	N = 319
	between		0.0334836	0.0011088	0.1835156	n = 29
	within		0.0346111	-0.1661914	0.3467245	T = 11
Subsidies	overall	3860.699	4243.361	0	19033.51	N = 319
	between		3475.044	0	13010.07	n = 29
	within		2511.958	-3038.229	14939.55	T = 11
One-Time Subsidies	overall	3537.386	4030.152	0	18663.29	N = 319
	between		3319.64	0	12370.75	n = 29
	within		2360.584	-3340.128	14616.24	T = 11
Rebate	overall	1961.882	3050.316	0	16300	N = 319
	between		2256.879	0	8309.091	n = 29
	within		2090.718	-4915.632	10002.19	T = 11
VAT	overall	326.3244	1226.426	0	7083.101	N = 319
	between		1144.655	0	5824.593	n = 29
	within		484.86	-1589.506	3050.17	T = 11
Point of Sales Tax	overall	1153.223	2552.691	0	13857.51	N = 319
	between		2495.102	0	11788.88	n = 29
	within		697.473	-1071.646	6187.253	T = 11
Income Tax	overall	95.95679	673.2979	0	5605.004	N = 319
	between		392.123	0	1983.183	n = 29
	within		551.729	-1887.226	3717.778	T = 11
Recurring Incentives	overall	323.3133	864.7677	0	12146.02	N = 319
	between		440.033	0	1793.048	n = 29
	within		748.5206	-807.6731	11236.65	T = 11
Charging Points Total	overall	3283.577	8246	0	66664	N = 319
	between		5636.925	19.63636	23072.91	n = 29
	within		6102.194	-19389.33	46874.67	T = 11
Fast Chargers	overall	346.8245	898.7076	0	7456	N = 319
	between		523.9059	0	1892.545	n = 29
	within		736.0906	-1545.721	5910.279	T = 11
Charging Points Total per 100km Highway	overall	159.5143	383.4443	0	3578.968	N = 319
	between		303.3466	2.149691	1539.145	n = 29
	within		240.6327	-844.0664	2199.337	T = 11
Fast Chargers per 100km Highway	overall	22.19925	78.9566	0	988.7189	N = 319
	between		50.96274	0	269.8418	n = 29
	within		60.98046	-247.4514	741.0764	T = 11
Electricity to Diesel Price	overall	0.0994366	0.0237409	0.0551923	0.1739604	N = 319
	between		0.0209028	0.0697496	0.1437885	n = 29
	within		0.0118509	0.0697496	0.1437885	T = 11
Trend	overall	7.608373	0.0015719	7.60589	7.610853	N = 319
	between		0	7.608373	7.608373	n = 29
	within		0.0015719	7.60589	7.610853	T = 11

Focusing first on the descriptive statistics of the main independent variables, they do not strongly deviate from those of the EV investigation. In general, the subsidies for BEVs are slightly higher than those of the EV analysis, which can be concluded when comparing the averages of the variable *Subsidies* reported in

Tables 8.18 and 8.1. For BEVs the subsidy mean is 3860 € and for the EV analysis it was with 3500 € about 360 € less. This result makes sense when considering that governments try to incentivise the purchase of BEVs more than those of PHEVs. On the contrary, the variables *POSTax* and *Recurring Subsidies* exhibit greater values in the descriptive statistics of the EVs, which means that they must be greater for PHEVs. A potential reason for this outcome is that the calculation of these incentives are often based on vehicle prices. When BEVs and PHEVs are exempt from a tax, the incentive is greater for the PHEV as the vehicle price difference of the considered PHEV and the comparable ICC is greater than those of the BEV and its ICC counterpart.

To illustrate the development of the amount of subsidies over time, Figure 8.6 has been prepared, which incorporates the same characteristics as Figure 8.5 with the sole difference that negative taxes are eliminated. A general observation that can be derived from the table is that the purchase of a BEV is not supported in Lithuania and the country Estonia has just begun to support the acquisition of an BEV with a considerable grant of 5000 € per vehicle. Moreover, it can be observed that most countries constantly increased the amount of subsidies over the last years. Nevertheless, significant differences in the amount of granted subsidies still exist between the countries in the year 2020, from Lithuania, the country that supports the development of the market the least from a financial incentives perspective, to Norway, providing purchase subsidies of almost 17000 € per vehicle.

Figure 8.6: BEV Subsidies



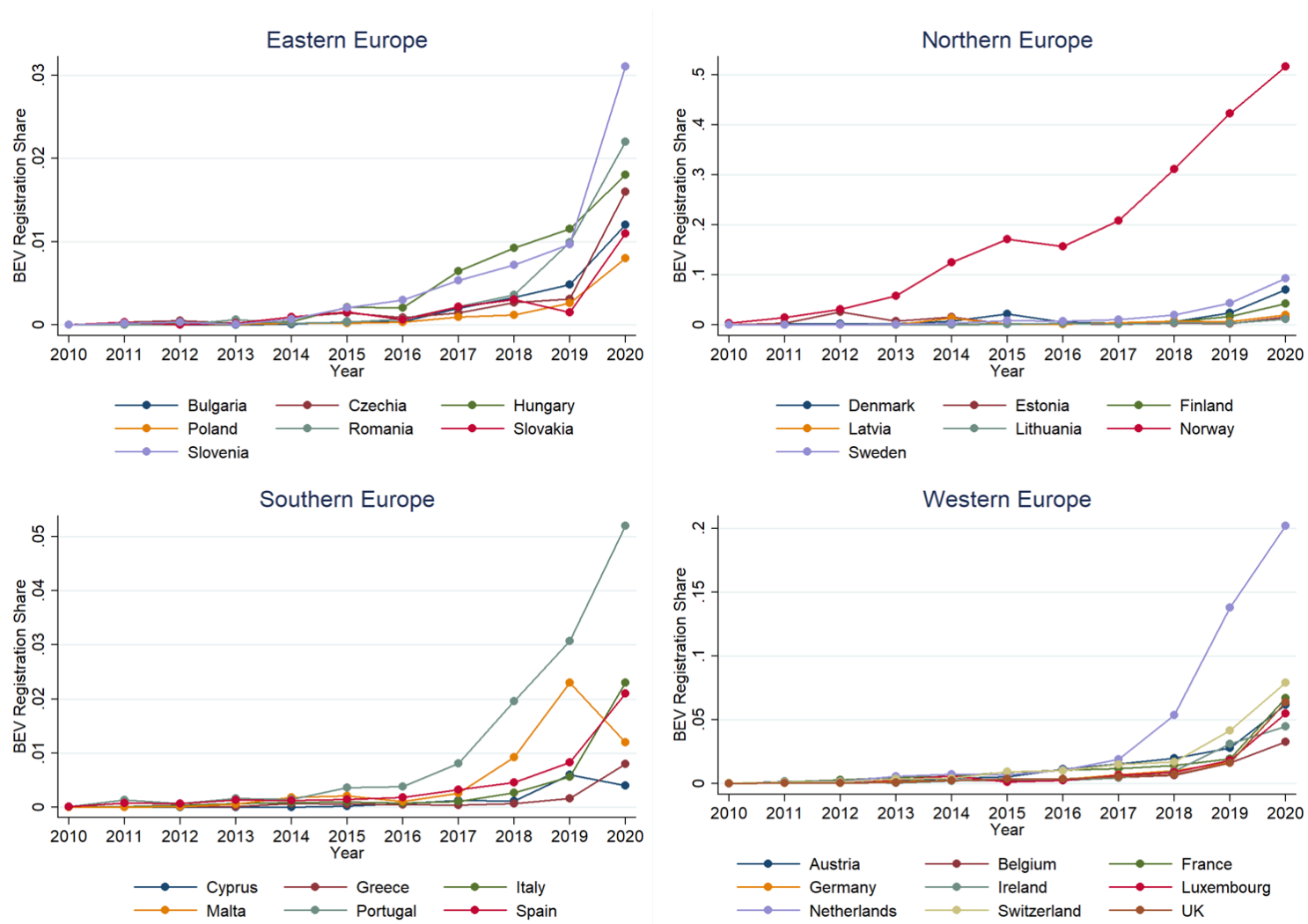
With the focus on BEVs in this part of the investigation, the dependent variable has also changed. While in all previous analyses the cumulative registration rate of new BEVs and PHEVs was considered, the dependent variable in this analysis is only represented by the registration rate of new BEVs. Consequently, it is not surprising that the overall mean of BEV registrations is with 0.014 smaller than the accumulated registration rate presented in the previous subchapter. Derived from the standard deviation and the between minimum and maximum, it can be concluded that there are also large country differences in the registration rate of BEVs. To better analyse the differences between countries and the development of the registration rate over time of this vehicle type, Figure 8.7 is prepared.

The registration rate of BEVs exhibits a strong growth rate, which is typical for innovative products that gradually enter the market. Thereby, the last three years and in particular the year 2020 are especially marked by a strong growth in registrations of this vehicle type. On average, the registrations have increased by 2.46% in absolute terms from 2019 to 2020, while the market has only increased by 0.06% in the previous year. This indicates that an exponential growth in the registration rate of BEVs is taking place and the product becomes a more established alternative to ICCs. With a registration rate of 51.60% in Norway in 2020, BEVs have already replaced ICCs as the prevalent vehicle type on the market. Putting the registration rate in conjunction with the amount of subsidies granted to BEV owners, this country also provides, based on the calculation applied in this research, the highest financial incentives for purchasing a car of this vehicle type. Another observation that can be made from Figure 8.7 is that only two countries recorded a negative growth in registrations for BEVs from the year 2019 to 2020. These countries are Cyprus and Malta and can be considered to be relatively small markets. For example, in Cyprus and Malta only 42 and 138 BEVs were newly registered in 2020. Thus, if only a few people decide to not purchase a BEV the registration rate will be heavily affected. Looking at the calculated amount of subsidies for these countries for the years 2019 and 2020, a slight but negative development can be recorded for both. The last point that is worth addressing at this stage is that compared to the total EV registration rate no strong downwards movements in the BEV registration rate can be observed for Netherlands in the years 2014, 2016 and 2017. Consequently, this means that the PHEV market has not developed equally in this country in these years. Moreover, the drop in the registration rates of PHEVs must have been higher than the gain in the registration rate of BEVs, to cause an

overall drop in the registration rate of EVs. This emphasises the need to analyse the markets separately from each other.

To empirically analyse whether subsidies also impact the registration rate of BEVs, the results of different statistical tests are presented in the following sections. Thereby, the nine model alternatives of the investigation of the aggregated EV market will also be used in this part of the analysis. The rationale behind using different models and the argumentation for the inclusion of the specific variables can thus be found in Chapter 8.1.1. There are, however, two differences in the models applied in this investigation compared to the ones defined in chapter 8.1.1. The first difference is that the dependent variable only considers the values of the BEV registration rate and is no longer represented by the aggregated amount of the BEV and PHEV registration rate. The second difference is in regard to the subsidies. Only the subsidies for BEVs are considered in this investigation and thus not the average amount of BEV and PHEV incentives is applied in the following analyses.

Figure 8.7: BEV Registration Rate



8.2.2 Pooled OLS

To obtain first insights into the relationship between the independent variables and the dependent variable, the nine model alternatives are regressed in a pooled OLS setting. All the regression models are run with robust standard errors to account for potential misspecification and the results are reported in Table 8.19.

First of all, when analysing the overall impact of the accumulated subsidies granted for BEVs, the impact stemming from those are highly significant and positive. This can be deduced from the coefficient of the variable *Subsidies* which is significant at a 1% level in all three groups. While the coefficient of the regression in the first group reports the highest influence of this determinant on the BEV market, the most conservative estimate is again obtained from the model in the third group. A potential explanation for the smaller coefficients of the third group *Subsidies* variable is the inclusion of the charging infrastructure determinant. The omission of this determinant might cause omitted variable bias and lead to the overestimation of the influence of subsidies in the first group of regressions.

When breaking down subsidies into one-time and recurring subsidies, differences in the effect of these subsidy types become evident. While the estimate for the *One-Time Subsidies* is highly significant in all groups, recurring subsidies seem to have no significant influence on the EV market. This in turn would mean that customers only consider one-time incentives when purchasing a BEV. Looking at the influence of the individual one-time incentives, the results of the Pooled OLS suggest that all one-time incentives exhibit a significant positive influence on the sales of BEVs. Only in the regression of the last group, the variable *Income Tax* seems to not significantly influence the BEV market.

All these findings are in line with the results obtained in Chapter 8.1.2. However, it can be seen that the magnitude of the different subsidies coefficients is for all variables in the regressions of the first and second group and for almost all variables in the third group lower in this investigation, implying differences in the effect of subsidies on the BEV market. A more thorough analysis of the coefficients will not take place at this stage as the panel property of the data set indicates that a Pooled OLS regression is not the correct model specification to analyse the present data set. To determine the model that suits the available data set the best, different diagnostic tests are performed in the following sections.

Table 8.19: Regression Results BEV Market: Pooled OLS

Variable	Group 1			Group 2			Group 3		
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)
Subsidies	0.0171%*** (0.00002)			0.0116%*** (0.00002)			0.0095%*** (0.00002)		
One-Time Subsidies		0.0174%*** (0.00002)			0.0119%*** (0.00002)			0.0097%*** (0.00002)	
Rebate			0.0096%*** (0.00003)			0.0100%*** (0.00002)			0.0059%*** (0.00002)
VAT			0.0473%*** (0.00006)			0.0282%*** (0.00006)			0.0302%*** (0.00004)
POSTax			0.0159%*** (0.00003)			0.0114%*** (0.00003)			0.0084%*** (0.00002)
Income Tax			0.0144%*** (0.00004)			0.0090%*** (0.00004)			0.0055% (0.00005)
Reoccurring Subsidies		0.0120% (0.00014)	0.0067% (0.00011)		0.0073% (0.00010)	0.00587% (0.00010)		0.0067% (0.00005)	0.0037% (0.00005)
LN(Electricity to Diesel Price)	0.468% (0.36622)	0.475% (0.36650)	0.630%* (0.35945)	0.499% (0.34390)	0.505% (0.34416)	0.580% (0.35230)	-0.104% (0.30138)	-0.098% (0.30183)	0.062% (0.30482)
Trend	2.9E+5%*** (46.687)	3.0E+5%*** (46.923)	3.6E+5%*** (43.537)	1.2E+5%*** (45.706)	1.2E+5%*** (43.817)	1.6E+5%*** (43.545)	8284.9%*** (46.373)	8307.5%*** (46.481)	13041.1%*** (46.406)
Chargers per 100km highway				0.1537%*** (0.00028)	0.1535%*** (0.00028)	0.1195%*** (0.00029)	0.4322%*** (0.04724)	0.4309%*** (0.04694)	0.3838%*** (0.04637)
Observations	294	294	294	294	294	294	249	249	249
F-score	169.49***	127.27***	95.27***	136.50***	107.94***	68.78***	134.69***	107.39***	94.42***
Overall R^2	0.6328	0.6333	0.6868	0.7077	0.7081	0.7160	0.7262	0.7265	0.7574

Note: The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$.

*** $p < 0.1$

** $p < 0.05$

* $p < 0.01$

8.2.3 Model Specification

The aim of this section in the investigation is to determine the model that fits the data the best. To answer this question this section of the analysis is divided into two parts. While the first part focuses on finding out what particular model specification should be applied; i.e. whether an FE or RE model is more appropriate, the Gauss-Markov OLS assumptions are checked in the second part. Since the models do not strongly deviate within a group, only the results of the most specific model (third model) are presented to avoid unnecessary repetition. If the models however, provide different results for the diagnostic tests it will be explicitly mentioned in the analysis. Diagnostic tests for all models can be found in Appendix K.

8.2.3.1 Fixed Effects vs. Random Effects Model

Before ruling out that a Pooled OLS is not the most suitable approach to investigate the data set at hand, two diagnostic tests, namely the F-Test and Breusch and Pagan (1979) LM Test, that are commonly used to analyse this question, are performed. Significant test results for all models of all groups for both the F-test (Table 8.20) and Breusch and Pagan (1979) LM test (Table 8.21) favor the application of a panel data regression. Thus, the results for the pooled OLS could as previously assumed be biased.

Table 8.20: F-Test

	Group 1	Group 2	Group 3
F	F(28, 258) = 14.33	F(28, 257) = 12.08	F(28, 212) = 6.09
Prob >F	0.0000	0.0000	0.0000

Table 8.21: Breusch and Pagan Lagrange Multiplier Test for Random Effects

	Group 1		Group 2		Group 3	
	Var	sd = sqrt(VAR)	Var	sd = sqrt(VAR)	Var	sd = sqrt(VAR)
EVR	3.770864	1.941871	3.770864	1.941871	2.740304	1.655386
e	0.5250056	0.7245727	0.5270444	0.7259782	0.4311201	0.6565973
u	0.6138863	0.7835089	0.4491914	0.6702175	0.2918065	0.5401912
	$\chi^2 (1)$	279.22	$\chi^2 (1)$	180.35	$\chi^2 (1)$	62.96
	Prob > χ^2	0.0000	Prob > χ^2	0.0000	Prob > χ^2	0.0000

In a next endeavour it is determined which particular panel data model provides the most reliable results. The common academic practice to decide between an FE and RE model would be to execute a Hausman specification test. Due to potential heteroskedasticity in the residuals a more valid approach is however to follow the

recommendation of (Wooldridge, 2010) and perform an augmented regression. The results of the augmented regression (Table 8.22) indicate that an FE specification should be applied to all models. This assumption is supported by the outcomes of the Hausman tests presented in Appendix K and the advantages this method entails to counteract the influence of potential omitted variable bias.

Table 8.22: Mundlak Approach for FE vs. RE

	Group 1	Group 2	Group 3
χ^2	$\chi^2 (6) = 98.91$	$\chi^2 (7) = 202.82$	$\chi^2 (8) = 77.28$
Prob > χ^2	0.0000	0.0000	0.0000

Based on the results, the nine econometric models that will be investigated in the main part of the analysis can be defined as follows:

Regressions Group 1:

$$(8.10) \quad \ln(BEV)_{it} = \beta_1 S_{it} + \beta_2 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_3 TR_{it} + \alpha_i + \epsilon_{it}$$

$$(8.11) \quad \ln(BEV)_{it} = \beta_1 OS_{it} + \beta_2 RS_{it} + \beta_3 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_4 TR_{it} + \alpha_i + \epsilon_{it}$$

$$(8.12) \quad \begin{aligned} \ln(BEV)_{it} = & \beta_1 R_{it} + \beta_2 VAT_{it} + \beta_3 PT_{it} + \beta_4 IT_{it} + \beta_5 RS_{it} \\ & + \beta_6 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_7 TR_{it} + \alpha_i + \epsilon_{it} \end{aligned}$$

Regressions Group 2:

$$(8.13) \quad \ln(BEV)_{it} = \beta_1 S_{it} + \beta_2 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_3 TR_{it} + \beta_4 CP_{it} + \alpha_i + \epsilon_{it}$$

$$(8.14) \quad \ln(BEV)_{it} = \beta_1 OS_{it} + \beta_2 RS_{it} + \beta_3 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_4 TR_{it} + \beta_5 CP_{it} + \alpha_i + \epsilon_{it}$$

$$(8.15) \quad \begin{aligned} \ln(BEV)_{it} = & \beta_1 R_{it} + \beta_2 VAT_{it} + \beta_3 PT_{it} + \beta_4 IT_{it} + \beta_5 RS_{it} \\ & + \beta_6 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_7 TR_{it} + \beta_8 CP_{it} + \alpha_i + \epsilon_{it} \end{aligned}$$

Regressions Group 3:

$$(8.16) \quad \ln(BEV)_{it} = \beta_1 S_{it} + \beta_2 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_3 TR_{it} + \beta_4 \ln(CP)_{it} + \alpha_i + \epsilon_{it}$$

$$(8.17) \quad \ln(BEV)_{it} = \beta_1 OS_{it} + \beta_2 RS_{it} + \beta_3 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_4 TR_{it} + \beta_5 \ln(CP)_{it} + \alpha_i + \epsilon_{it}$$

$$(8.18) \quad \begin{aligned} \ln(BEV)_{it} = & \beta_1 R_{it} + \beta_2 VAT_{it} + \beta_3 PT_{it} + \beta_4 IT_{it} + \beta_5 RS_{it} \\ & + \beta_6 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_7 TR_{it} + \beta_8 \ln(CP)_{it} + \alpha_i + \epsilon_{it} \end{aligned}$$

When comparing these models with those of the EV analysis in the previous chapter, it becomes evident that they are quite similar. Therefore, the variable definition for almost all variables can be derived from Table 8.7. It should however, be emphasised that as this investigation is concerned with the BEV market, the dependent variable of course reflects the registration rate of BEVs and the subsidy variables only the subsidies calculated for this vehicle type.

8.2.3.2 Gauss-Markov OLS Assumptions

As in the previous investigation, in the following the different regression models will be tested for multicollinearity, misspecification, heteroskedasticity and serial correlation. Starting with the issue of collinearity between the independent variables, a VIF test is applied. The results of the VIF test show that all variables for all models exhibit VIF scores under the critical threshold value of 10 as well as 5, respectively. Therefore, it can be concluded that none of the models are exposed to potential multicollinearity.

Table 8.23: VIF Test

Variable	Group 1		Group 2		Group 3	
	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
Rebate	1.12	0.894573	1.12	0.893240	1.18	0.846054
VAT	1.17	0.856958	1.70	0.587520	1.31	0.763994
Income Tax	1.04	0.961722	1.05	0.949569	1.08	0.925767
POSTax	1.18	0.845122	1.31	0.764179	1.39	0.719174
Recurring Subsidies	1.03	0.968302	1.03	0.967685	1.03	0.973220
LN(Electricity to Diesel Price)	1.06	0.946334	1.06	0.945381	1.10	0.912276
Trend	1.09	0.920319	1.23	0.815831	1.29	0.775059
Chargers per 100km			2.03	0.491589	1.69	0.593381
Mean VIF	1.10		1.32		1.26	

In a second step the models are tested for potential misspecification and omitted variable bias. Therefore, an Ramsey RESET test is applied which includes the powers 2, 3 and 4 of the predicted values into the regression models. The results obtained from the Ramsey RESET test are somewhat mixed not only between the groups but also within the groups. In the first group of regressions, only the third specification reports a p-value greater than 0.05 or 0.1, respectively, which allows the conclusion that this model is not misspecified. While this finding is in line with the results obtained from the EV investigation in the previous chapter, the models incorporating the untransformed charging infrastructure determinant also provide indications that these models are misspecified in the BEV case. The Ramsey RESET test is significant for all models, thus rejecting the null hypothesis to be correctly specified. Only the models of group 3 are all insignificant and can therefore be considered to be correctly specified.

Table 8.24: Ramsey RESET Test

	Group 1	Group 2	Group 3
F-score	F(3, 28) = 2.13	F(3, 28) = 7.15	F(3, 28) = 0.52
Prob >F	0.1187	0.0010	0.6710

To check for heteroskedasticity in the residuals of the models, visual analysis and a diagnostic test, in form of a likelihood ratio test, are applied in this part of the investigation as well. Both the residuals plotted against the predicted values (depicted in Figure 8.8) as well as the results of the diagnostic test (Table 8.25) provide evidence for the presence of heteroskedasticity in the residuals.

Figure 8.8: BEV Heteroskedasticity

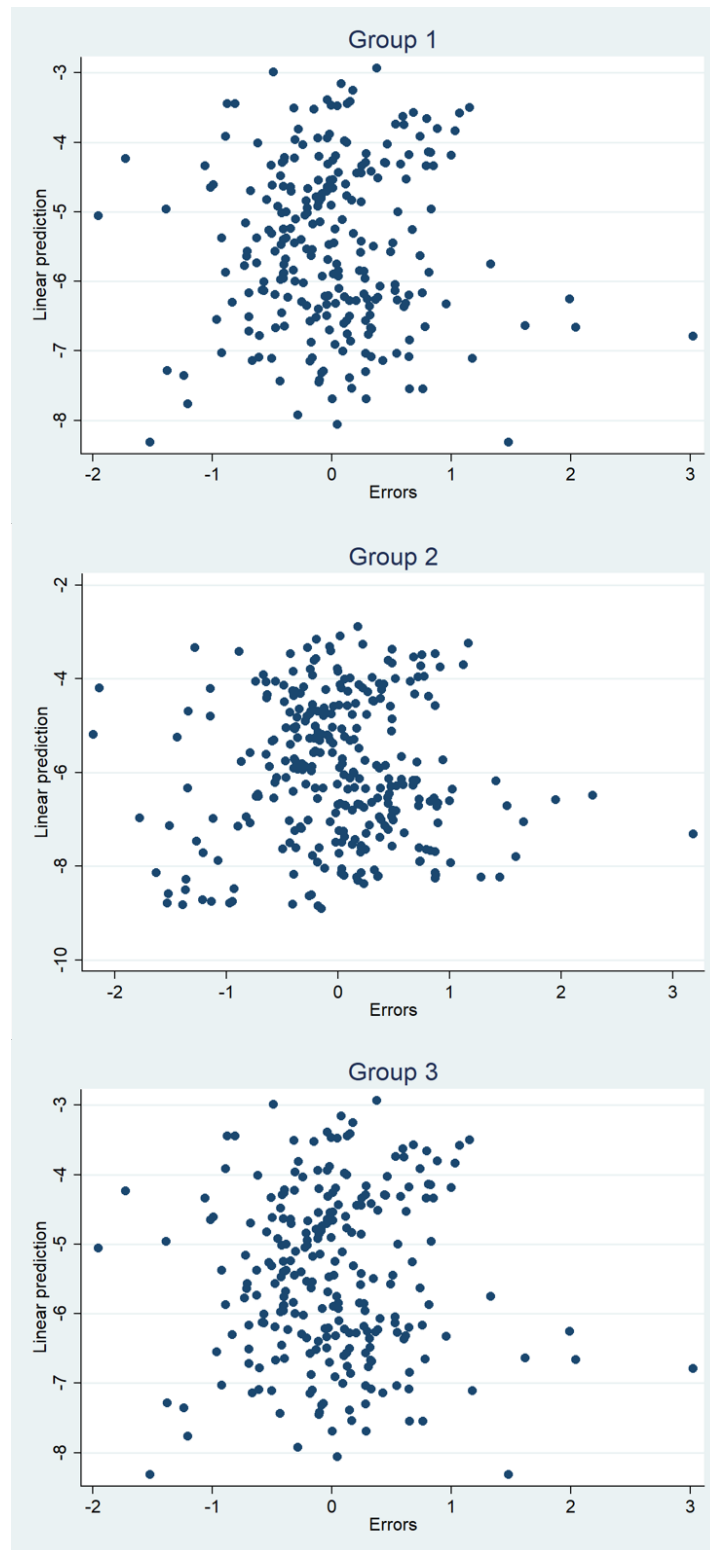


Table 8.25: Likelihood Ratio Test

	Group 1	Group 2	Group 3
χ^2	$\chi^2(28) = 79.02$	$\chi^2(28) = 103.68$	$\chi^2(28) = 106.04$
Prob $> \chi^2$	0.0000	0.0000	0.0000

Lastly, a Wooldridge test for autocorrelation shows that all models are serial correlated. To counteract the biases arising from heteroskedasticity and serial correlation, robust standard errors clustered at country level are applied to the FE models. Moreover, due to the potential misspecification of the models of Groups 1 and 2, it is assumed that the most reliable results, which are presented in the next chapter, are obtained from the regressions of group 3.

Table 8.26: Wooldridge Test for Autocorrelation

	Group 1	Group 2	Group 3
F	$F(1, 28) = 11.885$	$F(1, 28) = 11.877$	$F(1, 28) = 38.275$
Prob $> F$	0.0018	0.0018	0.0000

8.2.4 Panel Regression

With the knowledge obtained from the specification as well as diagnostic tests in the previous section, all models are run with an FE specification and robust standard errors clustered at country level. Although, the regressions of Groups 1 and 2 exhibited a significant Ramsey RESET test, the results of these regressions are reported to sustain the chance of a comparison of the results with those obtained from Group 3 and of the EV investigation. Moreover, when generally looking over the coefficients of the main independent variables, no large differences in the magnitude can be identified. Thus, the bias that might have arisen from a potential misspecification does not exhibit a too severe influence on the variables of interest.

First of all, evaluating the overall model fit, the R^2 value of all regressions is relatively high implying a good model fit of the data. The lowest R^2 values can be identified for the regressions of Group 3 which could be traced back to the observation loss due to the ln transformation of the charging infrastructure determinant. Nevertheless, an R^2 value of 0.7827 for the "weakest" model means that still 78.27% of the variance can be explained by the model.

Focusing on the main independent variables, it can be concluded that the amount of subsidies significantly influences the registration rate of BEVs. The aggregated *Subsidies* coefficient is reported to be positive and significant at a 1% level for all groups. Comparing the values of the FE estimation to those from

the pooled OLS, the coefficients have strongly decreased in magnitude, especially in the first specification of Group 1. This supports the choice to fit the data into an FE model as the estimates of the pooled OLS have seemingly suffered under omitted variable bias. Surprisingly, different to the Pooled regressions, the estimate of the main independent variable *Subsidies* in the third group is greater than the coefficients for this variable in Group 1 and 2. The magnitude of the difference is with 0.0007% however, not very large. Analysing the results of the second regression of the groups, the FE regressions provide evidence that both *One-Time Subsidies* as well as *Recurring Subsidies* exhibit a significant influence on the BEV market. While *One-Time Subsidies* are significant at a 5% level in each group, the determinant *Recurring Subsidies* strongly loses in significance and magnitude in the regression of Group 3 and is only significant at a 10% level. Comparing the coefficients of *One-Time Subsidies* and *Recurring Subsidies* with each other, the impact stemming from *Recurring Subsidies* seems to be bigger, especially in the first two groups. The difference between these two determinants however, diminishes in the regression of Group 3. When looking at the results of the models considering the individual components of *One-Time Subsidies*, apart from the determinant *Rebate* all other factors of this category do not significantly influence the BEV market. The coefficient of the variable *Rebate* is significant at a 1% level and exhibits a similar impact on the BEV market, regardless of the group a regression belongs to. According to the results of Model 8.18 the influence of *Rebate* on the BEV registration rate even succeeds the impact of *Recurring Subsidies*, which can be derived from the smaller coefficient of the latter variable in the third group of regressions. Based on the assumption that this model provides the most reliable estimates as it does not exhibit any signs of being misspecified, it can be concluded that one time subsidies in form of rebates are the best measure to accelerate the BEV market. Nevertheless, it should be kept in mind that the implications that can particularly be obtained from the last regression of each group is limited. Due to the lack of observations for subsidies on such a detailed level, the validity of the results can be questioned. For example, due to the transformation of the charging infrastructure variable and the resulting loss of observations, only a single country is left in the regression that included values for the variable *Income Tax*. This has also caused that the F-score could not be estimated for this regression. A comparison between the results obtained in this investigation and those from the investigation focusing on the EV market will not take place at this stage. It has

been decided to accommodate an separate sub-chapter for such a discussion.

Moving on with the analysis, the results of the regressions performed with an FD approach, that can be found in Table 8.28 are now briefly described. Since more reliable results are expected to be obtained from the FE regressions, only major differences are presented in this investigation. A major difference between the estimates of the FE and FD approach lies in the significance of the variable *Recurring Subsidies*. In contrast to the results of the FE analysis, this variable turns out to be insignificant when applying an FD approach. Other dissimilarities in regard to the significance of variables between these specifications can be found in the coefficients of the variables *VAT* and *Income Tax*. The estimate of the variable *VAT* is with the FD specification unlike the estimate of the FE approach, significant at a 10% level for the regression of the Groups 1 and 3. Moreover, the determinant representing the amount of subsidies obtained through *Income Tax* reduction turns out to exhibit a significant influence on the BEV market, when looking at the results of Group 3. The interpretation of these results should also be made cautiously as the same issue of reliability of the results stemming from the third model of the groups applies also to the estimates obtained from an FD specification. In particular, the significance of the *Income Tax* variable is questionable in this research. In general, the results of the FD regressions are in line with those of the FE specification. Most importantly applying this model specification, the result also provide evidence that the aggregated amount of subsidies exhibit a significant influence on the BEV market.

A final discussion of the results will take place at the end of the entire chapter to avoid unnecessary repetitions with the findings for the other vehicle types. Moreover, it allows a more stringent comparison of the findings of the corresponding sub-chapters. In the following section the robustness of the findings will be tested.

Table 8.27: Regression Results BEV Market: Fixed Effects Models

Variable	Group 1			Group 2			Group 3		
	Model 8.10	Model 8.11	Model 8.12	Model 8.13	Model 8.14	Model 8.15	Model 8.16	Model 8.17	Model 8.18
Subsidies	0.0059%*** (0.00002)			0.0060%*** (0.00002)			0.0066%*** (0.00002)		
One-Time Subsidies		0.0055%** (0.00002)			0.0056%** (0.00002)			0.0065%** (0.00003)	
Rebate			0.0073%*** (0.00002)			0.0073%*** (0.00002)			0.0076%*** (0.00003)
VAT			-0.0019% (0.00008)			-0.0019% (0.00008)			0.0070% (0.00009)
POSTax			-0.0013% (0.00007)			-0.0011% (0.00008)			0.0006% (0.00007)
Income Tax			-0.0021% (0.00002)			-0.0021% (0.00002)			-0.0006% (0.00004)
Recurring Subsidies		0.0088%*** (0.00002)	0.0096%*** (0.00002)		0.0087%*** (0.00002)	0.0096%*** (0.00002)		0.0072%* (0.00004)	0.0072%** (0.00003)
LN(Electricity to Diesel Price)	-0.733% (0.64809)	-0.757% (0.65287)	-0.752% (0.65732)	-0.761% (0.64191)	-0.783% (0.64661)	-0.754% (0.65194)	-0.824% (0.63963)	-0.829% (0.65287)	-0.841% (0.67462)
Trend	1.4E+6%*** (45.724)	1.4E+6%*** (46.464)	1.5E+6%*** (47.838)	1.6E+6%*** (52.418)	1.7E+6%*** (52.907)	1.5E+6%*** (52.101)	2.3E+5%*** (109.28)	2.4E+5%*** (110.19)	2.4E+5%*** (124.01)
Chargers per 100km highway				-0.0168% (0.00030)	-0.0164% (0.00029)	-0.0010% (0.00029)	0.0975% (0.09357)	0.0976% (0.09388)	0.1022% (0.10394)
Observations	294	294	294	294	294	294	249	249	249
F-score	315.81***	238.33***	64352.48***	274.67***	219.23***	21518.41***	108.81***	87.06***	n.a.
Within R^2	0.8221	0.8223	0.8250	0.8226	0.8227	0.8250	0.7827	0.7827	0.7848
Between R^2	0.0001	0.0000	0.1370	0.0103	0.0127	0.1388	0.1404	0.1376	0.0394
Overall R^2	0.5612	0.5583	0.4827	0.5392	0.5370	0.4822	0.5571	0.5562	0.5105

Note: Country Fixed Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** p < 0.01

** p < 0.05

* p < 0.1

Table 8.28: Regression Results BEV Market: First Differences Models

Variable	Munzel			Charger			log charger		
	Model 8.10	Model 8.11	Model 8.12	Model 8.13	Model 8.14	Model 8.15	Model 8.16	Model 8.17	Model 8.18
Subsidies	0.0053%*** (0.00002)			0.0053%** (0.00002)			0.0057%*** (0.00002)		
One-Time Subsidies		0.0062%** (0.00002)			0.0062%** (0.00002)			0.0072%*** (0.00002)	
Rebate			0.0066%** (0.00003)			0.0066%** (0.00003)			0.0081%** (0.00003)
VAT			0.0074%* (0.00004)			0.0072% (0.00004)			0.0095%* (0.00005)
POSTax			-0.0007% (0.00006)			-0.0006% (0.00006)			-0.0012% (0.00006)
Income Tax			0.0134% (0.00010)			0.0136% (0.00010)			0.0053%* (0.00003)
Recurring Subsidies		0.0022% (0.00002)	0.0020% (0.00002)		0.0022% (0.00007)	0.0020% (0.00002)		0.0015% (0.00002)	0.0014% (0.00002)
LN(Electricity to Diesel Price)	-1.062%* (0.59920)	-1.034% (0.61138)	-0.996% (0.62922)	-1.063%* (0.59971)	-1.035% (0.61202)	-0.995% (0.62974)	-0.789% (0.59142)	-0.762% (0.60314)	-0.748% (0.62392)
Trend	1.0E+7%*** (59.661)	9.5E+6%*** (59.802)	9.2E+6%*** (60.450)	1.2E+7%*** (73.510)	1.1E+7%*** (73.957)	1.1E+7%*** (73.918)	8.6E+5%*** (94.834)	6.9E+5%*** (97.302)	6.6E+5%*** (98.265)
Chargers per 100km				-0.0201% (0.00035)	-0.0202% (0.00035)	-0.0204% (0.00034)	0.0479% (0.09531)	0.0635% (0.09469)	0.6097% (0.09652)
Observations	265	265	265	265	265	265	220	220	220
F-score	263.67***	170.64***	115.03***	197.58***	136.74***	103.04***	114.69***	99.79***	n.a.
Overall R^2	0.3670	0.3685	0.3708	0.3673	0.3689	0.3712	0.3708	0.3759	0.3798

Note: Fixed Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** p < 0.01

** p < 0.05

* p < 0.1

8.2.5 Robustness Tests

To check for the robustness of the results, the same tests as for the EV market are performed. Hence in the first robustness test the trend variable is replaced by time dummies. In the second robustness test dynamic panel data models are applied to control for a potential overestimation of the results from the main part of the analysis. Finally, the time frame of the investigation is limited to analyse potential changing significance and magnitudes of the *Subsidies* coefficients.

8.2.5.1 Time Dummies

The robustness of the results for the BEV market are again initially tested by replacing the trend variable with time dummies and thus establishing a two-way fixed effects model. The results of the FE regressions with the time dummies can be seen in Table 8.29. Focusing on the main independent variables and starting with the aggregated subsidies regression, the estimates are in line with the results of the main part of the investigation presented in Table 8.27 in terms of significance and coefficient values. The coefficient values are only slightly higher in the regressions with the dummy variables with a maximum difference of 0.0006% for the regressions of the first and second group. For the *One-Time Subsidies* and *Rebate* determinant the significance and magnitude of the coefficients have increased, when comparing to the estimates obtained in the main part of the investigation, confirming the effect of these determinants on the BEV market. On the contrary, the significance of the determinant *Recurring Subsidies* has deteriorated in comparison to the previous results in several regression alternatives. Moreover, the influence has lost in magnitude and exhibits a difference of up to 0.0032% for the last regression model of Group 3. Except for the second regression of Group 3 the estimates of this variable are however all significant and positive implying that although the influence of *Recurring Subsidies* is not as strong as initially expected, it nevertheless exhibits a significant influence on the sales of this vehicle type. As in the EV analysis, the significance and the increase in the value of the estimates support the inclusion of a trend variable in the regressions for the BEV market. In conclusion, this robustness test supports the findings of the main part of the investigation.

Table 8.29: Regression Results BEV Market: Fixed Effects with Time Dummies

Variable	Group 1			Group 2			Group 3		
	Model 8.10	Model 8.11	Model 8.12	Model 8.13	Model 8.14	Model 8.15	Model 8.16	Model 8.17	Model 8.18
Subsidies	0.0065%*** (0.00002)			0.0066%*** (0.00002)			0.0064%*** (0.00002)		
One-Time Subsidies		0.0065%*** (0.00002)			0.0066%*** (0.00002)			0.0067%** (0.00002)	
Rebate			0.0081%*** (0.00002)			0.0080%*** (0.00002)			0.0072%*** (0.00003)
VAT			0.0013% (0.00008)			0.0012% (0.00008)			0.0132% (0.00011)
POSTax			-0.0006% (0.00007)			0.0001% (0.00008)			0.0005% (0.00007)
Income Tax			0.0028% (0.00003)			0.0029% (0.00003)			-0.0001% (0.00004)
Recurring Subsidies		0.0065%** (0.00002)	0.0069%*** (0.00002)		0.0063%** (0.00002)	0.0069%*** (0.00002)		0.0045% (0.00003)	0.0040%* (0.00002)
LN(Electricity to Diesel Price)	0.0182% (0.68924)	0.0185% (0.69673)	0.0610% (0.69398)	-0.0294% (0.66749)	-0.0280% (0.67520)	0.0440% (0.68329)	-0.2854% (0.66811)	-0.2712% (0.67904)	-0.2329% (0.66822)
Chargers per 100km highway				-0.0185% (0.00030)	-0.0186% (0.00030)	-0.0046% (0.00030)	0.1328% (0.10724)	0.1321% (0.10739)	0.1512% (0.12134)
Time Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	294	294	294	294	294	294	249	249	249
F-score	144.54***	138.77***	153.82***	188.13***	174.36***	209.80***	126.09***	108.90***	n.a.
Within R^2	0.8665	0.8665	0.8683	0.8670	0.8670	0.8683	0.8268	0.8270	0.8291
Between R^2	0.0004	0.0004	0.1408	0.0176	0.0173	0.1519	0.2788	0.2852	0.2651
Overall R^2	0.6007	0.6007	0.5297	0.5757	0.5759	0.5277	0.6125	0.6149	0.6123

Note: Country Fixed Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** p < 0.01

** p < 0.05

* p < 0.1

8.2.5.2 Dynamic Regression Models

Dynamic panel data regressions are also performed in this part of the investigation as an additional robustness test to control for potential issues arising from endogeneity in the model and to account for the natural growth of this innovative technology. As in the EV investigation only the regressions with the aggregated *Subsidies* variable are considered. The first dynamic panel data model applied in this part of the investigation is a difference GMM following Arellano and Bond (1991). The decision to execute a difference instead of a system GMM is based on the upper and lower bounds estimates for the first lag of the dependent variable. These are again determined by the estimates of this variable obtained in an OLS and FE model.

Different specifications in terms of lag length and SE specifications are tested for the GMM model and the results of the most appropriate model are reported in Table 8.30.³ The quality of the specifications is again assessed based on the test results of the second order autocorrelation as well as the Hansen test. Furthermore, following the recommendation of Roodman (2009), models with a lower number of instruments are favoured if *ceteris paribus*. The final specifications can be seen in Table 8.30 and in general coincide with those applied to the GMM model of chapter 8.1.5.2.

Evaluating the diagnostic tests of the models, the second order correlation as well as the Hansen test exhibit the aspired insignificant test results for the three different regressions. Moreover, the probability score of the Hansen J statistic is not too high so that it can be assumed that the right set of instruments are applied and the models are not overidentified. Focusing now on the main independent variable *Subsidies*, the reported coefficients are all highly significant and positive, supporting the findings of the main part of this investigation. When comparing the estimates to the estimates of the FE model in Table 8.27, the results obtained from the GMM approach are however smaller in magnitude. Thus, including a lagged dependent variable into the model and running a GMM approach provides evidence that an FE approach could over-report the influence of granted financial incentives on the BEV market, as it was the case in the EV investigation.

³The results of other GMM models with different specifications can be found in Appendix L

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Table 8.30: Results BEV Market: Difference GMM

Variable	Group 1	Group 2	Group 3
L.ln(EV registration share)	0.5646%*** (0.14111)	0.5844%*** (0.12100)	0.3616% (0.21527)
Subsidies	0.0044%*** (0.00001)	0.0043%*** (0.00001)	0.0050%*** (0.00002)
LN(Electricity to Diesel Price)	-0.0736% (0.71544)	-0.0045% (0.70077)	-0.1055% (0.79796)
Chargers per 100km		-0.0190% (0.00043)	0.1204% (0.08669)
Yearly Time-Dummies	✓	✓	✓
Two-step GMM	✓	✓	✓
Robust	✓	✓	✓
Windmeyer correction	✓	✓	✓
Orthogonal	✓	✓	✓
Observations	236	236	217
F-score	222.45***	257.82***	489.25***
Number of Instruments	20	21	21
Instruments (lags used)	EV (1)	EV (1)	EV (1)
AR(2) probability	0.280	0.275	0.602
Hansen test	0.164	0.141	0.235
FE Lower Bound	0.2933	0.2934	0.2933
OLS Upper Bound	0.7504	0.6953	0.6409

The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** p < 0.01

** p < 0.05

* p < 0.1

In light of the data set, in this investigation an LSDVC dynamic panel data model might be better suited than a GMM approach as it presents better abilities to cope with the biases arising from a relatively small sample. Consequently, this dynamic panel data model is applied as a second robustness test in this part of the analysis. The model is further specified with an Arellano and Bond (1991) bias correction as well as a bootstrap with 100 repetitions is applied to estimate the variance-covariance matrix.

Table 8.31: Results BEV Market: LSDVC Models

Variable	Group 1	Group 2	Group 3
L.ln(EV registration share)	0.4138%*** (0.06549)	0.4056%*** (0.06486)	0.4130%*** (0.06527)
Subsidies	0.0055%*** (0.00002)	0.0057%*** (0.00002)	0.0051%*** (0.00002)
LN(Electricity to Diesel Price)	-0.2672% (0.42812)	-0.3024% (0.43171)	-0.5933% (0.49334)
Chargers per 100km		-0.0167% (0.00018)	0.1025%* (0.05261)
Yearly Time-Dummies	✓	✓	✓
Bias correction	AB estimator	AB estimator	AB estimator
Bootstrap number	100	100	100

The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. AB stands for Arellano and Bond (1991).

*** p < 0.01

** p < 0.05

* p < 0.1

Based on the results reported in Table 8.31, a significant influence of *Subsidies* on the BEV market can also be concluded in this model setting. The obtained estimates for this variable are significant at a 1% level and positive in each of the regressions. While the magnitude of the estimates from the LSDVC models are lower compared to the estimates obtained from the FE approach, they are higher than the reported coefficients approximated with the GMM approach. This result suggests that the FE models over-report the influence of *Subsidies* on the BEV market but not to the extent the results obtained from the GMM approach might indicate. Furthermore, the difference in the estimates for this determinant between the FE and LSDVC approach is almost negligible for the first two groups. In particular, the difference in the coefficients is only 0.0004% and 0.003% for the regressions of Group 1 and 2, respectively. In contrast, the estimate from the LSDVC approach for the variable *Subsidies* in the third group is closer to the coefficient calculated with a GMM specification and only deviates by 0.0001% (0.0051% - 0.0050%). It therefore exhibits a greater difference to the FE estimate with approximately 0.0015% (0.0066% - 0.0051%). In conclusion, it can be assumed that the FE approach only slightly over-reports the influence of financial incentives on the BEV market.

8.2.5.3 Limited Time Frame

To check whether subsidies exhibited a stronger influence on the registration rate of BEVs in the early years of this market as it was the case for the aggregated EV market, the years 2018, 2019 and 2020 are omitted in this robustness test. Again due to the smaller data set only the LSDVC and FE models of Group 1 are investigated, which excludes all regressions with the charging infrastructure determinant. Furthermore, the model with the detailed level of one-time subsidies is also not considered in this part of the investigation. This leaves in total three different regression models the results of which are reported in Table 8.32.

First of all looking at the significance of the coefficients, all estimates for the main independent variables exhibit significant results supporting the general hypothesis that subsidies are an important determinant for the diffusion of EVs in the market. In contrast to the results from the EV analysis, the difference between the subsidy variables with the reduced time frame and the results from the main analysis is not as large for BEVs, when focusing on the FE model with the aggregated subsidy variable (Model 8.10). The estimates only deviate by about

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0.0001%. However, on the contrary a larger difference between the estimates can be found in the LSDVC models. The coefficient approximated for the time frame 2010 to 2017 is 0.002% larger, which can be considered substantial when keeping in mind the actual effect of this determinant. Hence, for the case of the BEV market it cannot certainly be concluded that the effect of subsidies on the BEV market has diminished over the last years.

Table 8.32: Results BEV Market: Time Frame 2010-2017

Variable	LSDVC	Model 8.10	Model 8.11
L.ln(EV registration share)	0.3082%*** (0.08188)		
Subsidies	0.0075%*** (0.00002)	0.0060%** (0.00002)	
One-Time Subsidies			0.0052%** (0.00003)
Recurring Subsidies			0.0104%*** (0.00002)
LN(Electricity to Diesel Price)	-1.3084%* (0.74961)	-2.0563%** (0.75787)	-2.1007%*** (0.75087)
Trend		2.8E+6%*** (50.3891)	2.9E+6%*** (51.0647)
Yearly Time-Dummies	✓		
Bias correction	AB estimator		
Bootstrap number	100		
Observations		207	207
F-score		284.44	238.33
Within R^2		0.7069	0.7077
Between R^2		0.0024	0.0054
Overall R^2		0.3175	0.3087

The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. AB stands for Arellano and Bond (1991).

*** p < 0.01

** p < 0.05

* p < 0.1

8.3 Plug-in Hybrid Electric Vehicle

In this part of the investigation the effect of subsidies on the PHEV market is analysed. As discussed in the literature review, PHEVs incorporate next to an internal combustion motor also an electrical drive-train. Thus, this vehicle type does not completely depend on an electrical propulsion system and therefore is not a completely CO_2 neutral alternative to ICCs. Consequently, as many researchers have found out, the possibility exists that the purchase of a PHEV can be driven by different factors compared to BEVs (Wee et al., 2018; Narassimhan and Johnson, 2018). It is also possible that while the determinants of the market might be the same, the importance in terms of the actual magnitude of the effects of the determinants might differ between the vehicle types. Therefore, it makes sense to also analyse if the PHEV market is significantly influenced by the amount of granted subsidies and in case it is, to determine what the magnitude of the influence is. In addition, the importance of this research is further supported when considering that a multitude of countries limit the amount of subsidies they grant for the purchase of a PHEV since this vehicle type is unlike a BEV not a CO_2 neutral alternative when operated.

8.3.1 Descriptive Statistics

As in the previous chapter, an initial discussion about the identified subsidies of the sample countries takes place. Therefore, it has been decided to first put the unprocessed data, which allows the amount of subsidies to be negative, in the scope of this investigation. Depicted in Figure 8.9, the calculated amount of subsidies granted for the purchase of PHEVs for all countries considered in this analysis over the time period 2010 to 2020 can be seen. What is striking in this illustration is that negative values for the aggregated *Subsidies* variable can be identified for three countries (Cyprus, Greece and Poland). All of these countries do not only exhibit a negative amount for one but for several years so that in total ten observations with negative incentives exist. Interestingly, nine of these observations also exhibited a negative amount for the investigation of the EV market and only two for the BEV market. This means that the negative subsidies amount of the PHEVs outweighed the positive subsidies amount of the BEVs in six cases. In contrast, only once the positive amount of BEV subsidies superseded the negative incentives of the PHEVs and resulted in a positive subsidies amount for the aggregated EV case.

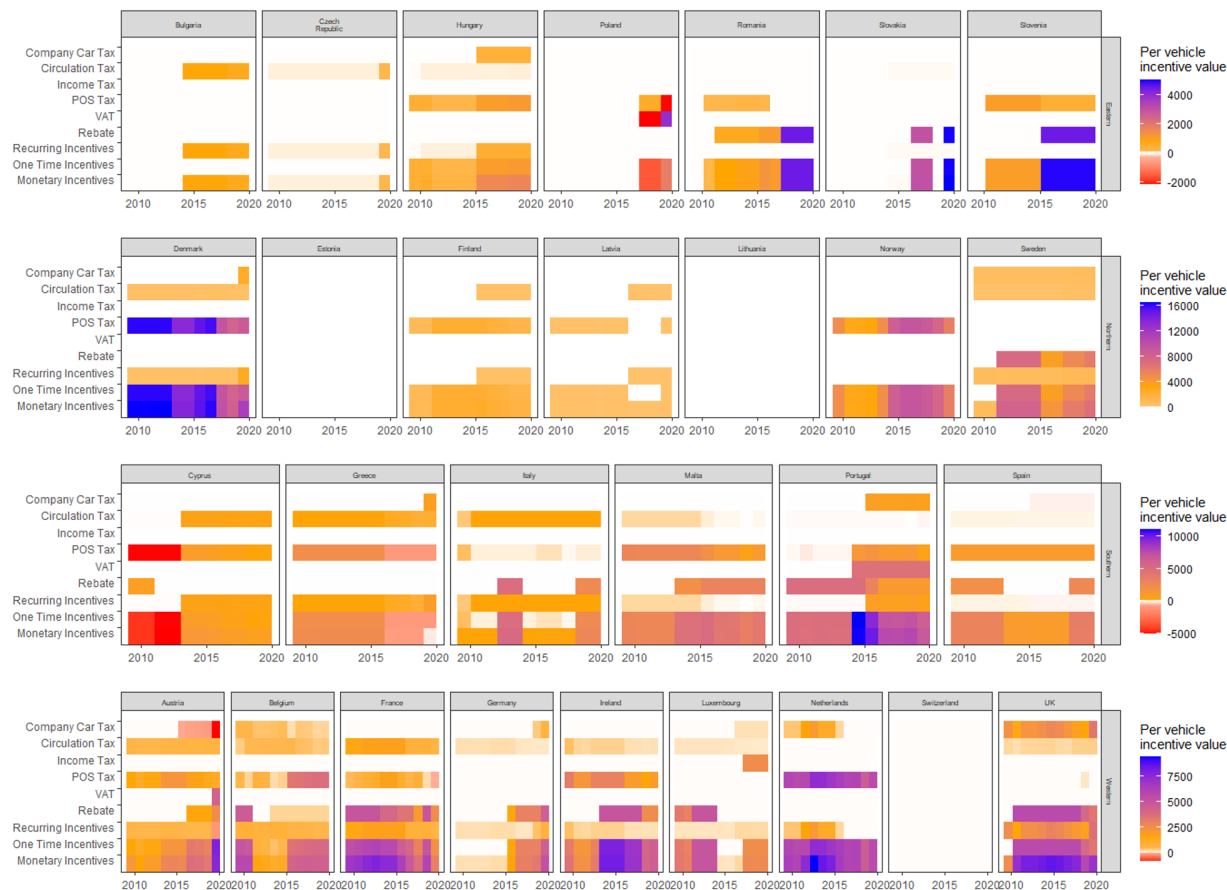
The reason why the amount of subsidies for the PHEV outweighed the subsidies of the BEVs emphasises again the issue when the calculation of a tax consists of different components which reflect different attributes of a car. To recall, an EV experiences a substantial disadvantage in the calculation of a tax if it considers car attributes in which ICCs are by default better positioned (e.g. weight of an EV) or exhibit a temporary advantage such as the vehicle price. The latter can be assumed to decrease in magnitude as the technology of EVs advances. Nevertheless, since a PHEV incorporates an electric engine next to a fully equipped internal combustion motor and thus seems to be an advanced ICC, it is questionable whether a PHEV will ever be available for the same price as a comparable ICC. In this investigation the price gap between the PHEV and its comparable ICC is larger than the considered BEV and its ICC counterpart. Using the Excise tax in Poland as an example, the calculation of which has already been explained in chapter 8.1.1, illustrates that the larger price gap of PHEVs paired with the lower rate of reductions that are granted for this vehicle type result in more negative subsidies than for BEVs. Thus, it can be concluded that PHEVs can be more exposed to the negative effects of taxes that consider different car attributes than BEVs if the tax does not sufficiently account for the disadvantages of this vehicle type with an adequate reduction.

Considering that a comprehensive discussion with examples of the drawbacks when employing different car attributes, where EVs exhibit substantial disadvantages compared to ICCs, as components for the calculation of a tax has already taken place in the previous sections and partly in this paragraph, only a few examples for the PHEV case where this disadvantage becomes evident once again will be touched upon now. The first example is the registration tax levied in Greece. While BEVs are exempt from the registration tax in Greece, buyers of PHEVs are granted a reduction on their taxes. In particular, the tax is levied based on the vehicle purchasing price which is multiplied by a basic coefficient that also depends on the purchasing price, and multiplied by a CO_2 based coefficient. The basic coefficient of PHEVs is reduced by 50%. However, since the PHEV is considerably more expensive than the considered ICC, the starting basic coefficient is already twice as high as the one of the ICC. Hence, the 50% reduction only causes that the same basic coefficient will be applied to both vehicle types. Since the PHEV is more expensive than the ICC, the taxes are nevertheless more expensive for the PHEV (ACEA, 2020).

Another example is the excise tax in Poland. For the year 2020, the tax incentive is calculated with an amount of -2,139 €. The reason for such a high negative incentive is again the higher purchasing prices of PHEVs and a disadvantage regarding a car attribute the government not sufficiently accounted for. The calculation of the excise tax is based on the vehicle value and a tax rate that is determined depending on the motor size. Although, an ICC faces a higher tax rate than a PHEV if the motor size is similar, the tax does not sufficiently account for the commonly larger motors of PHEVs. Hence by incorporating a motor that is bigger than 2,000cc the PHEV is taxed with a rate of 9.3% while the comparable ICC only equipped with a motor smaller than 2,000cc is taxed with a rate of 3.0%.

In general smaller negative incentive amounts can also be found for the circulation tax in Portugal and Cyprus and the causes traced back to similar issues. The amounts are only smaller because the taxes in general are smaller in absolute terms since they occur annually. Lastly negative company car tax incentives are also identified in the countries Austria and Spain. Both of these negative amounts are caused by the considerably higher price of the considered PHEV in the data collection approach.

Figure 8.9: PHEV Subsidies with Negative Amounts



Note: Structure of the illustration is based on Münzel et al. (2019). Focus of this graphic should be on the negative amount of subsidies. Since a continuous scale is used to present the amount of subsidies in the graphics, amounts that are close to 0 might also be illustrated in white. Therefore, it is recommended to also refer to the graphic that depicts the amount of subsidies where negative values have been eliminated to obtain a clearer picture of the amount of subsidies.

Since negative subsidies do not incentivise the purchase of a PHEV, these subsidies were eliminated from the sample and are hence not considered in this investigation. Consequently, subsidies that are left in the data set should be positive. Looking at the descriptive statistics in Table 8.33, the minimum of each individual subsidy indeed does not fall below 0, verifying that data processing has been successful.

Table 8.33: Descriptive Statistics: PHEV Market

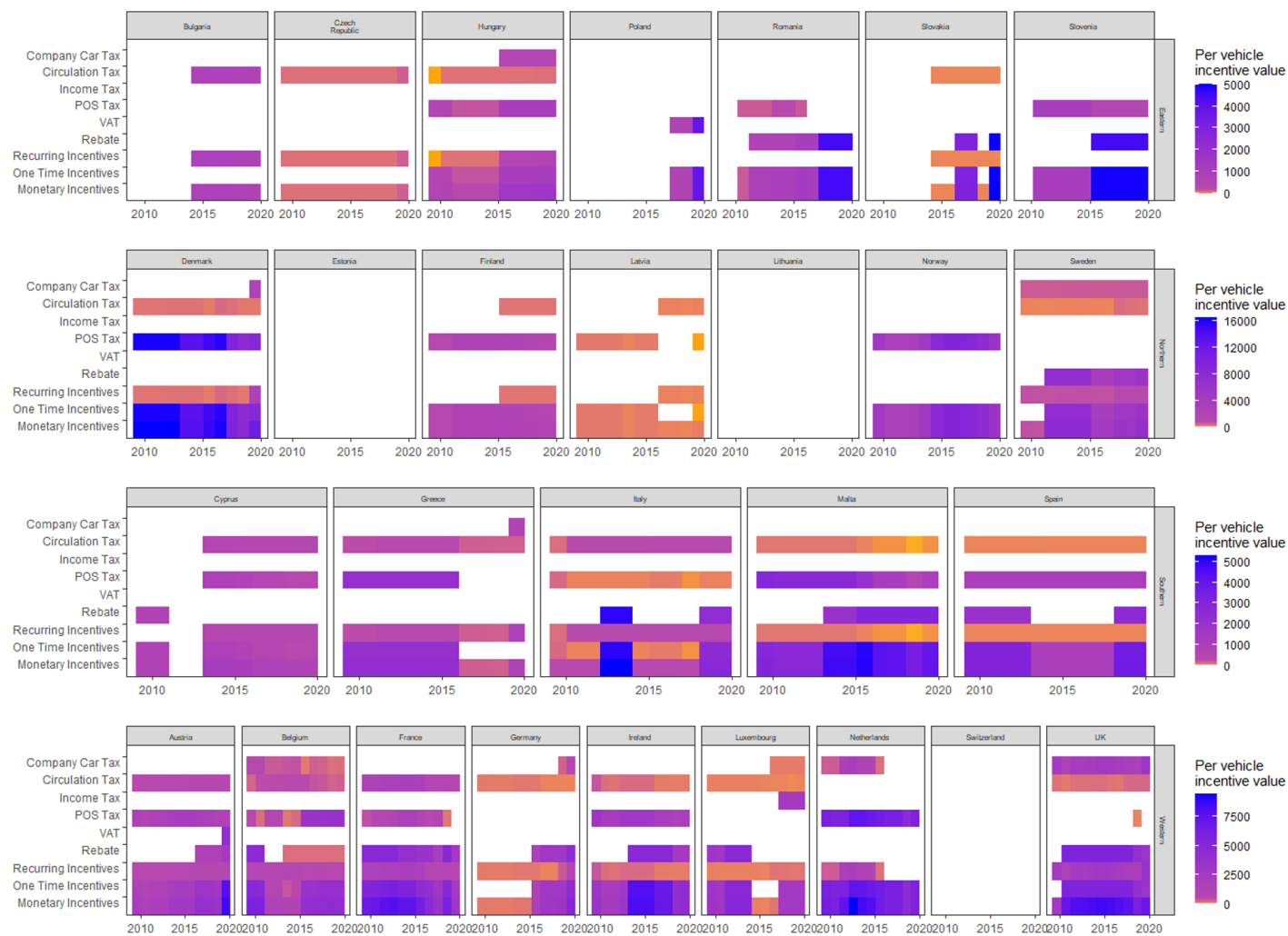
Variable		Mean	Std. Dev.	Min	Max	Observations
PHEV Registration Share	overall	0.0104417	0.0294191	0	0.229	N = 319
	between		0.0170898	0.0007265	0.0844493	n = 29
	within		0.0241373	-0.0740075	0.1955361	T = 11
Subsidies	overall	3064.532	3478.724	0	16403.59	N = 319
	between		3164.449	0	13991.39	n = 29
	within		1550.815	-2633.118	8386.512	T = 11
One-Time Subsidies	overall	2737.488	3278.479	0	16111.75	N = 319
	between		2948.66	0	13482.55	n = 29
	within		1525.531	-2681.581	7974.595	T = 11
Rebate	overall	1166.453	1966.249	0	7377.262	N = 319
	between		1503.036	0	4816.127	n = 29
	within		1295.399	-3649.674	5166.453	T = 11
VAT	overall	116.6887	707.6794	0	4656.717	N = 319
	between		478.6803	0	2540.027	n = 29
	within		528.0916	-2423.339	3963.127	T = 11
Point of Sales Tax	overall	1430.836	2915.798	0	1611.75	N = 319
	between		2824.589	0	13482.55	n = 29
	within		879.0108	-3988.234	4545.432	T = 11
Income Tax	overall	23.51097	241.677	0	2500	N = 319
	between		126.6105	0	681.8182	n = 29
	within		207.0788	-658.3072	1841.693	T = 11
Recurring Subsidies	overall	327.0442	567.1904	0	3632.166	N = 319
	between		510.8934	0	2453.233	n = 29
	within		262.4897	-575.2504	2582.727	T = 11
Charging Points Total	overall	3283.577	8246	0	66664	N = 319
	between		5636.925	19.63636	23072.91	n = 29
	within		6102.194	-19389.33	46874.67	T = 11
Fast Chargers	overall	346.8245	898.7076	0	7456	N = 319
	between		523.9059	0	1892.545	n = 29
	within		736.0906	-1545.721	5910.279	T = 11
Charging Points Total per 100km Highway	overall	159.5143	383.4443	0	3578.968	N = 319
	between		303.3466	2.149691	1539.145	n = 29
	within		240.6327	-844.0664	2199.337	T = 11
Fast Chargers per 100km Highway	overall	22.19925	78.9566	0	988.7189	N = 319
	between		50.96274	0	269.8418	n = 29
	within		60.98046	-247.4514	741.0764	T = 11
Electricity to Diesel Price	overall	0.0994366	0.0237409	0.0551923	0.1739604	N = 319
	between		0.0209028	0.0697496	0.1437885	n = 29
	within		0.0118509	0.0697496	0.1437885	T = 11
Trend	overall	7.608373	0.0015719	7.60589	7.610853	N = 319
	between		0	7.608373	7.608373	n = 29
	within		0.0015719	7.60589	7.610853	T = 11

Focusing first on the main independent variables, the presumption expressed in the previous investigation that PHEVs exhibit for almost all subsidies lower amounts than BEVs can be confirmed. This is not surprising since the amount of subsidies calculated for the EV investigation presents an average of the subsidies

calculated for BEVs and PHEVs. As the BEV subsidies exhibited greater values compared to the corresponding subsidies for EVs, the PHEV subsidy values must exhibit the smaller values.

Considering the standard deviation of the aggregated *Subsidies* variable in relation to the population average, a large variation in the amount of subsidies across the countries over the considered time period can also be recognised. This claim is further supported when looking at the between minimum and maximum of the sample. While at least one country exists that did not issue any subsidies for PHEVs over the investigated time period, another country has granted on average over the eleven years almost 14,000 €. To better analyse the difference of subsidies for this vehicle type between the countries and the development of the amount, Figure 8.10 is prepared. As it can be derived from Figure 8.10 three countries did not grant any subsidies for PHEVs over the entire investigated time period. These countries are Estonia, Lithuania and Switzerland. In contrast, based on the calculation methodology applied in this study, the country that granted the most subsidies for PHEVs was Denmark with 16,403 €. Surprisingly, this amount of subsidies was not recorded in the year 2020 but in the year 2013. This leads to another observation that was already made in the EV analysis. Several countries exhibit higher amounts of subsidies not at the end but in one year during the investigated time period. Two reasons could have potentially impacted the peak in subsidies for several countries before the end of the investigated time period. One reason is as discussed in the EV subsidies analysis that levied taxes are inflexible and not often adjusted in several countries. Thus for example CO_2 based taxes lose their efficiency with the further development of ICCs. The other reason could be that governments specifically aim to reduce the financial support of the acquisition of a PHEV as they increasingly want to foster the development of the BEV market. When for example focusing on the issued rebates in western countries, which already exhibit a relatively high registration rate of EVs, it can be noticed that countries such as Belgium, France, Ireland or the UK have reduced the granted amounts. Moreover, Luxembourg has completely stopped to grant rebates for the purchase of PHEVs after 2014.

Figure 8.10: PHEV Subsidies



Focusing now on the PHEV market, the dependent variable of the investigation has changed as well. With an average of 1.04% of all new registrations being a PHEV, this market exhibits overall a smaller registration rate than the BEV market. Moreover, although a maximum registration rate of 22.9% in a country in one year suggests that this vehicle type has reached a competitive position in at least one country, the highest recorded registration rate for BEVs is more than twice as high. Another indication that suggests that BEVs are more appealing to people than PHEVs can be derived from the between minimum and maximum values of these vehicle types reported in the descriptive statistics. For both between minimum and maximum the descriptive statistics of the PHEV market exhibit a lower value. Especially the between maximum of the PHEV registration rate is smaller by an amount of 0.1, meaning that the country with the on average highest registration rate reported 10% less PHEV registration than the country with the highest BEV registration rate. To be able to make more advanced analyses about the development of the market and discussions about potential differences between the PHEV and BEV market, the PHEV registration rates for each country over time is plotted in Figure 8.11.

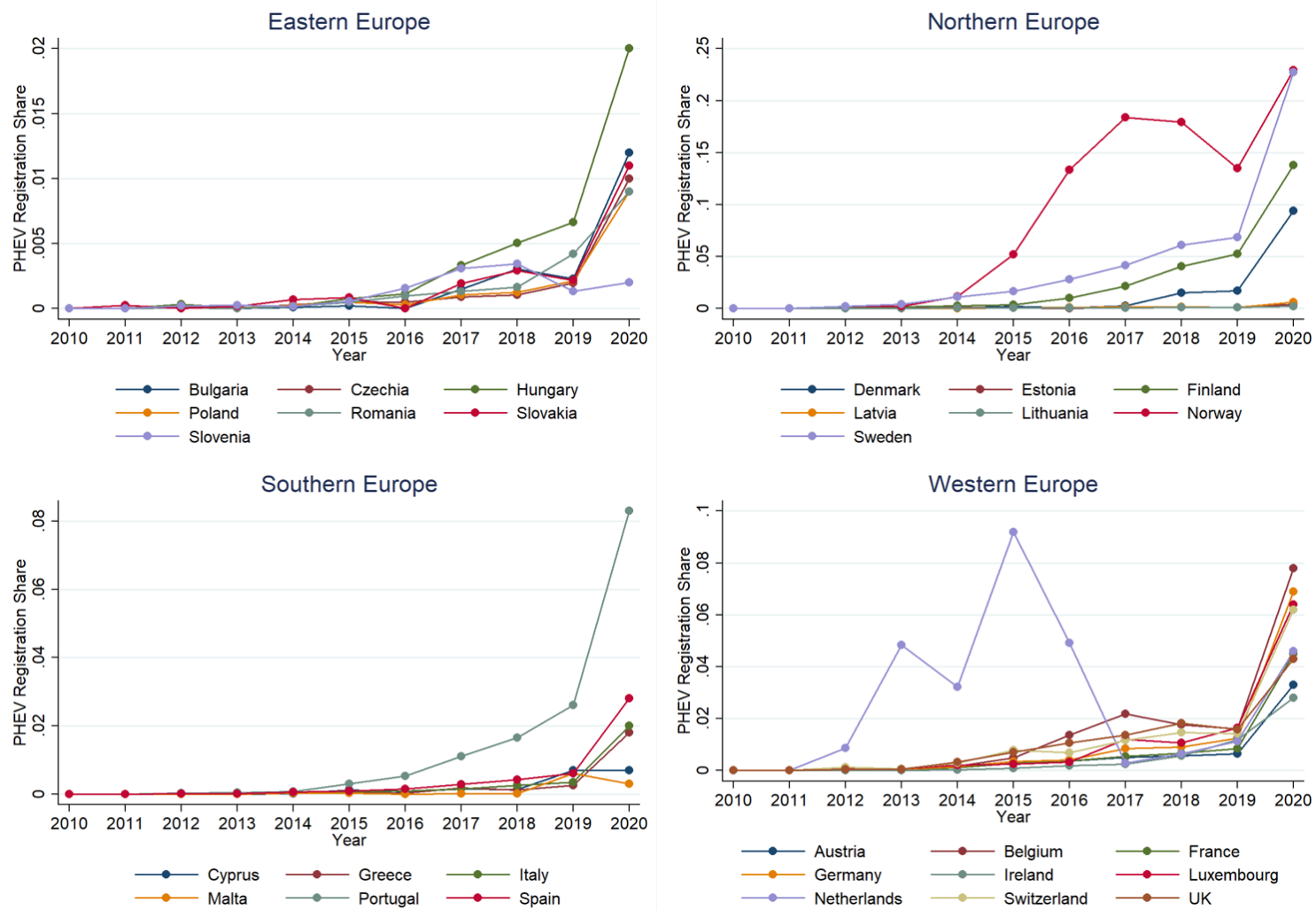
As in the previous investigations, a general increase of the registration rate can also be identified for the PHEV vehicle type. Focusing on the early years of the market, the annual registration rate of this vehicle type was close to 0 for all countries in the sample. While the market has evolved after a few years in most of the countries, changes in the registration rate were only barely recognisable in some of the countries. This is especially noticeable in the southern European countries. Starting from 2015 most of the countries have however witnessed an upwards moving trend with exponential growth in the last year of the considered time period. Comparing the development of the PHEV market with the BEV market, some interesting differences can be identified for several countries. In contrast to what the descriptive statistics suggest there is however, no evidence that all countries generally favour BEVs over PHEVs. Moreover, while the registration rate of BEVs was higher in 23 countries in 2019, the number has decreased to 16 countries in 2020. An interesting development of the PHEV market can be observed in the Netherlands. While the registration rate of the BEV market has gradually increased over the last years the registration rate of PHEVs exhibits strong up and down movements. The up and down movements in this market have also caused the same pattern in the EV market investigation for this country. In contrast to

all other countries in the PHEV market as well as BEV market, the rate of new registrations has peaked relatively early in 2015 with 9.9% and not reached the same level again.

Another interesting observation that can be made from Figure 8.11 is that with a difference of 0.2% Norway and Sweden exhibit almost the same registration rate for PHEVs in 2020. In contrast, there is a large difference in the registration rate of BEVs between these two countries. Putting this into relation with the amount of subsidies, a potential explanation could be the difference in the amount of subsidies granted for each vehicle type issued in the countries. The difference in the calculated amount of subsidies between BEVs and PHEVs in this study is substantially higher in Norway than in Sweden. Consequently, people could tend more strongly to purchase an BEV in Norway as they would waive to obtain more incentives when purchasing a PHEV than potential customers of a PHEV in Sweden.

Considering all these differences and keeping in mind that BEVs and PHEVs are eventually competing products on the market, this might suggest that subsidies could have a different influence on the PHEV market than on the BEV market. In the following, different statistical approaches are applied to empirically analyse the influence of subsidies on the PHEV registration rate. For the empirical analyses the exact same nine model composition in terms of included variables as in the previous investigations are used in this analysis. The reason for using different models and the considered variables for each model can therefore be found in the descriptive statistics of the EV analysis. Since this investigation is concerned with the influence of subsidies on the PHEV market, the dependent variable has changed and reflects the registration rate of the PHEV market. Furthermore, only the granted subsidies for PHEVs are considered in this study.

Figure 8.11: PHEV Registration Rate



8.3.2 Pooled OLS

To gain initial insights about the potential influence and magnitude of the considered subsidies on the PHEV market the data at hand is in a first analysis regressed in a pooled OLS setting. To account for potential misspecifications all regressions are run with robust standard errors. The results of the regressions are reported in Table 8.34. Like in the investigation of the EV as well as BEV market, the results of the coefficients of the aggregated subsidies variable suggests a highly significant and positive influence of this determinant on the PHEV market. This result is obtained for each regression in the three groups. Breaking down the subsidies based on whether they are granted once or more frequently, the results show that both positively impact the PHEV market. The coefficients of the determinants *One-Time Subsidies* as well as *Recurring Subsidies* are significant at a 1% level in almost all regressions. Only in the third group of regressions, the significance level of *One-Time Subsidies* deteriorates, the estimate is nevertheless still significant at a 10% level. Comparing the results for these two determinants with those of the BEV investigation, presents an interesting finding. While *Recurring Subsidies* appeared to have an insignificant influence on the registration rate of BEVs in Chapter 8.2.2, based on the results of Table 8.34 this determinant turns out to be highly significant to explain changes in the registration rate of PHEVs. Therefore, the Pooled OLS regression of the models already provides initial evidence that there might be a difference in the effect of the subsidy types on the registration rates of these vehicles. Interestingly the coefficient of the *Recurring Subsidies* variable can be considered relatively high in this investigation. Using the most conservative estimate for this determinant, which is presented in Model (8), a 1,000€ increase in subsidies would cause an increase in the registration rate by 46.9%.

The estimates of the individual one-time subsidies are relatively consistent in terms of significance for the regressions of Groups 1 and 2. Apart from *Rebate*, each variable exhibits coefficients that are positive and significant either at a 1% or 5% level. In contrast, the results of the regression of Group 3 that distinguishes between different one-time subsidies, suggests that *POSTax* as well as *Income Tax* exhibit next to *Rebate* no significant influence on the PHEV market. Focusing on the determinant *Rebate*, the outcomes of the regressions provide more evidence for potential differences between the BEV and PHEV market, in regard to the influence of subsidies on the respective markets. In contrast to the BEV market, the coefficient of *Rebate* is not significant in this investigation. Further analyses

of the results will not take place at this stage as a pooled OLS is as in the previous investigations assumed to be not the best specification for the data set at hand. Consequently, the next parts of this investigation are dedicated to finding the most suitable econometric specifications of these models for the given data set.

Table 8.34: Regression Results PHEV Market: Pooled OLS

Variable	Group 1			Group 2			Group 3		
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)
Subsidies	0.0173%*** (0.00003)			0.0134%*** (0.00003)			0.0090%*** (0.00003)		
One-Time Subsidies		0.0144%*** (0.00004)			0.0090%*** (0.00003)			0.0060%* (0.00003)	
Rebate			0.0070% (0.00005)			0.0060% (0.00005)			-0.0009% (0.00005)
VAT			0.0180%*** (0.00004)			0.0231%*** (0.00005)			0.0214%*** (0.00005)
POSTax			0.0167%*** (0.00005)			0.0088%*** (0.00004)			0.0068% (0.00004)
Income Tax			0.0415%*** (0.00009)			0.0233%*** (0.00009)			0.0147% (0.00012)
Recurring Subsidies		0.0536%*** (0.00015)	0.0636%*** (0.00015)		0.0625%*** (0.00016)	0.0662%*** (0.00017)		0.0469%*** (0.00015)	0.0551%*** (0.00015)
LN(Electricity to Diesel Price)	0.795%** (0.35581)	0.718%** (0.34420)	0.769%** (0.34829)	0.899%*** (0.32970)	0.803%** (0.31634)	0.821%** (0.32971)	0.627%* (0.32755)	0.559%* (0.31665)	0.629%* (0.32388)
Trend	1.0E+7%*** (72.514)	1.0E+7%*** (72.002)	9.4E+6%*** (73.032)	3.5E+6%*** (73.249)	3.3E+6%*** (72.928)	2.8E+6%*** (74.127)	4.5E+5%*** (91.918)	4.5E+5%*** (90.678)	3.6E+5%*** (91.611)
Chargers per 100km highway				0.1224%*** (0.00023)	0.1334%*** (0.00024)	0.1347%*** (0.00025)	0.3437%*** (0.06513)	0.3427%*** (0.06560)	0.3465%*** (0.06775)
Observations	264	264	264	264	264	264	243	243	243
F-score	124.37***	106.01***	86.08***	106.56***	86.98***	83.16***	87.30***	76.55***	62.99***
Overall R^2	0.5876	0.5961	0.6029	0.6305	0.6459	0.6491	0.5980	0.6099	0.6180

Note: The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$.

*** p < 0.1

** p < 0.05

* p < 0.01

8.3.3 Model Specification

In the light of finding the most suitable model specification for the given data set, different statistical analyses are applied in the following. The process starts with determining the best panel data model and continues with tests that are supposed to check whether the Gauss-Markov OLS assumptions are met with the selected specification. Following the style of the previous chapters, only the test results of the third regression of each group are presented to avoid unnecessary repetition. The results of all regressions of all groups are nevertheless reported in Appendix N. In case differences of the results within a group exist, these are also reported in this chapter.

8.3.3.1 Fixed Effects vs. Random Effects Model

To test for the poolability of the data, an F-Test (Table 8.35) as well as Breusch and Pagan (1979) LM (Table 8.36) are applied. Significant results of both tests for all regressions of all groups reject the null hypothesis of poolability and suggest that a panel data model approach should be applied.

Table 8.35: F-Test

	Group 1	Group 2	Group 3
F	F(28, 228) = 10.43	F(28, 227) = 8.24	F(28, 206) = 9.94
Prob >F	0.0000	0.0000	0.0000

Table 8.36: Breusch and Pagan Lagrange Multiplier Test for Random Effects

	Group 1		Group 2		Group 3	
	Var	sd = sqrt(VAR)	Var	sd = sqrt(VAR)	Var	sd = sqrt(VAR)
EVR	5.031856	2.24318	5.031856	2.24318	4.196034	2.048422
e	1.010424	1.005199	1.014625	1.007286	0.8010383	0.8950074
u	0.8112047	0.900669	0.6092456	0.7805419	0.9342283	0.9665549
	$\bar{\chi}^2(1)$	245.42	$\bar{\chi}^2(1)$	125.04	$\bar{\chi}^2(1)$	151.20
	<u>Prob > $\bar{\chi}^2$</u>	0.0000	<u>Prob > $\bar{\chi}^2$</u>	0.0000	<u>Prob > $\bar{\chi}^2$</u>	0.0000

To determine which panel data specification is the most suitable for the data set, an augmented regression is run. The reason to carry out an augmented regression instead of a Hausman test is the potential presence of heteroskedasticity in the residuals. Results of the Hausman test for this model can however also be found in Appendix N. While the results of the augmented regression for the third model in all groups as presented in Table 8.37 generally favour the application of an FE approach, the results for the first two regressions of Group 1 suggest that

the application of an RE model is also a valid alternative. Despite this result, in this investigation it is decided to also fit the data of these regressions into an FE specification to ensure the comparability of the results. To justify this approach, it should be recalled what the idea behind a Hausman test or augmented regression is. These diagnostic tests check whether the coefficients of an RE model are significantly different than those of an FE model. If this is not the case, it can be assumed that the RE model does not suffer from omitted variable bias and thus distorts the estimates of the coefficients (Hausman, 1978; Schunck, 2013). Hence, applying an FE approach instead of an RE approach will provide estimates that are more conservative in terms of their significance level but do not significantly differ in their magnitude. A positive and important side effect is that this approach also directly controls for unobserved time-invariant country differences.

Table 8.37: Mundlak Approach for FE vs. RE

	Group 1	Group 2	Group 3
χ^2	$\chi^2 (6) = 42.44$	$\chi^2 (7) = 105.09$	$\chi^2 (8) = 100.98$
Prob > χ^2	0.0000	0.0000	0.0000

Determining that an FE specification is the most appropriate model alternative for the data set, explicit econometric models can be defined. As in the previous chapter nine different models which can be categorised into three groups are analysed throughout this part of the investigation. The difference between the groups is concerned with the charging infrastructure determinant, while the models within the groups differ based on their level of detail of the *Subsidies* variable.

Regressions Group 1:

$$(8.19) \quad \ln(PHEV)_{it} = \beta_1 S_{it} + \beta_2 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_3 TR_{it} + \alpha_i + \epsilon_{it}$$

$$(8.20) \quad \ln(PHEV)_{it} = \beta_1 OS_{it} + \beta_2 RS_{it} + \beta_3 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_4 TR_{it} + \alpha_i + \epsilon_{it}$$

$$(8.21) \quad \begin{aligned} \ln(PHEV)_{it} = & \beta_1 R_{it} + \beta_2 VAT_{it} + \beta_3 PT_{it} + \beta_4 IT_{it} + \beta_5 RS_{it} \\ & + \beta_6 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_7 TR_{it} + \alpha_i + \epsilon_{it} \end{aligned}$$

Regressions Group 2:

$$(8.22) \quad \ln(PHEV)_{it} = \beta_1 S_{it} + \beta_2 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_3 TR_{it} + \beta_4 CP_{it} + \alpha_i + \epsilon_{it}$$

$$(8.23) \quad \ln(PHEV)_{it} = \beta_1 OS_{it} + \beta_2 RS_{it} + \beta_3 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_4 TR_{it} + \beta_5 CP_{it} + \alpha_i + \epsilon_{it}$$

$$(8.24) \quad \begin{aligned} \ln(PHEV)_{it} = & \beta_1 R_{it} + \beta_2 VAT_{it} + \beta_3 PT_{it} + \beta_4 IT_{it} + \beta_5 RS_{it} \\ & + \beta_6 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_7 TR_{it} + \beta_8 CP_{it} + \alpha_i + \epsilon_{it} \end{aligned}$$

Regressions Group 3:

$$(8.25) \quad \ln(PHEV)_{it} = \beta_1 S_{it} + \beta_2 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_3 TR_{it} + \beta_4 \ln(CP)_{it} + \alpha_i + \epsilon_{it}$$

$$(8.26) \quad \ln(PHEV)_{it} = \beta_1 OS_{it} + \beta_2 RS_{it} + \beta_3 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_4 TR_{it} + \beta_5 \ln(CP)_{it} + \alpha_i + \epsilon_{it}$$

$$(8.27) \quad \begin{aligned} \ln(PHEV)_{it} = & \beta_1 R_{it} + \beta_2 VAT_{it} + \beta_3 PT_{it} + \beta_4 IT_{it} + \beta_5 RS_{it} \\ & + \beta_6 \ln\left(\frac{EP}{DP}\right)_{it} + \beta_7 TR_{it} + \beta_8 \ln(CP)_{it} + \alpha_i + \epsilon_{it} \end{aligned}$$

Since the general model specification and the definition of the considered variables has not changed compared to Chapters 8.1.3.1 and 8.2.3.1, they can be derived from Table 8.7. What should be noticed is however is that the dependent variable and the subsidies reflect the PHEV market.

8.3.3.2 Gauss-Markov OLS Assumptions

After determining that an FE specification should be used to model the different regressions, it is now checked whether the models comply with the Gauss-Markov OLS assumptions. First of all, a VIF test is carried out to identify potential multicollinearity between the independent variables. VIF scores below 5 suggest that none of the regressions is affected by multicollinearity.

Table 8.38: VIF Test

Variable	Group 1		Group 2		Group 3	
	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
Rebate	1.26	0.794485	1.26	0.793434	1.33	0.751171
VAT	1.03	0.971496	1.04	0.965149	1.03	0.971854
Income Tax	1.04	0.960072	1.05	0.950950	1.06	0.940686
POSTax	1.08	0.925341	1.30	0.770124	1.37	0.731003
Recurring Subsidies	1.20	0.832140	1.20	0.831433	1.21	0.826886
LN(Electricity to Diesel Price)	1.06	0.939921	1.06	0.939423	1.08	0.928024
Trend	1.06	0.944652	1.18	0.851060	1.37	0.728743
Chargers per 100km			1.34	0.748882	1.63	0.611990
Mean VIF	1.10		1.18		1.26	

In a second test, the models are tested for misspecification and omitted variables. For this purpose a Ramsey RESET test is executed. In this Ramsey RESET test the powers 2, 3 and 4 of the predicted values are added to the regression models and checked whether the joint inclusion of these terms provide additional explanatory power. In contrast to the investigations of the previous chapters, none of the considered models exhibits a significant Ramsey RESET test statistic in this analysis. Even all regression models of Group 1, in which at least one model was always significant in the studies for the EV and BEV market, are now insignificant. This provides evidence that all models are correctly specified.

Table 8.39: Ramsey RESET Test

	Group 1	Group 2	Group 3
F-score	F(3, 28) = 0.55	F(3, 28) = 0.67	F(3, 28) = 0.99
Prob >F	0.6531	0.5772	0.4101

Another important OLS requirement is the absence of heteroskedasticity in the residuals. To check for homoskedastic residuals, a visual analysis as well as a diagnostic test in form of a likelihood ratio test is performed. While the graphs of the plotted residuals against the predicted values in Figure 8.12 already exhibit first indications for potential heteroskedasticity in the residuals, these presumptions are eventually confirmed by the significant likelihood ratio tests.

Figure 8.12: PHEV Heteroskedasticity

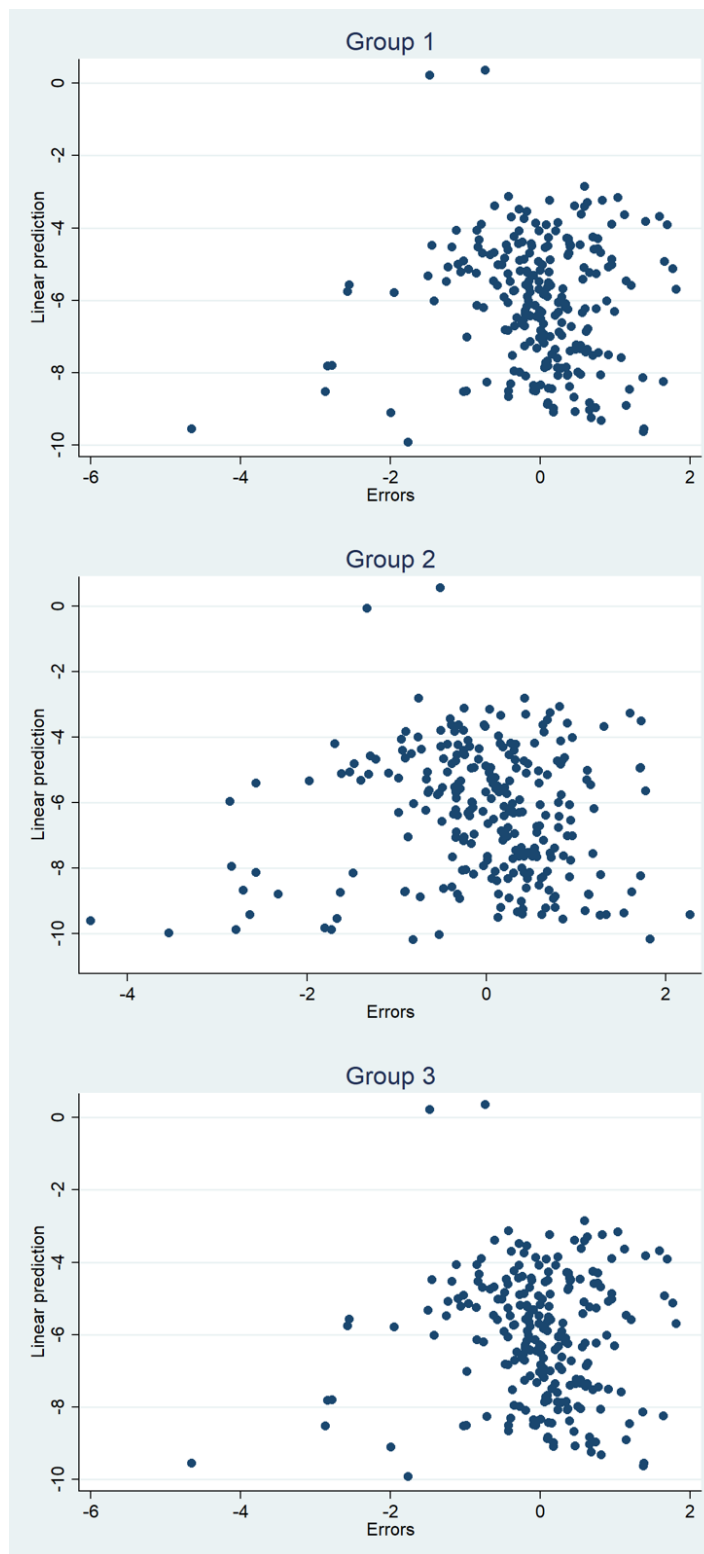


Table 8.40: Likelihood Ratio Test

	Group 1	Group 2	Group 3
χ^2	$\chi^2(28) = 113.69$	$\chi^2(28) = 108.33$	$\chi^2(28) = 155.08$
Prob $> \chi^2$	0.0000	0.0000	0.0000

The last diagnostic test is a Wooldridge test for autocorrelation and is supposed to test for serial correlation in the errors. Significant p-values of this test, as they can be seen in Table 8.41, indicate that as in the previous chapters also the regression models for the PHEV market are affected by serial correlation. To counteract the issues that could arise of heteroskedastic and serial correlated residuals, it has been decided to follow the recommendation of Wooldridge (2010) and apply robust standard errors clustered at the country level to the models.

Table 8.41: Wooldridge Test for Autocorrelation

	Group 1	Group 2	Group 3
F	F(1, 28) = 21.775	F(1, 28) = 21.729	F(1, 28) = 13.373
Prob $> F$	0.0001	0.0001	0.0010

8.3.4 Panel Regression

As opposed to the investigations for the EV and BEV market, the Ramsey RESET test provides no indication of misspecification for any of the regression models considered in this part of the analysis. Hence, all models should provide reliable results. However, it should be kept in mind that the $\ln$ transformation of the charging infrastructure determinant leads to a loss in observations. Therefore it can be assumed that the estimates for the variables of the first two groups are closer to the population truth.

Before starting with the description of the estimates for the individual determinants, an initial look should be cast on the explanatory power of the models. Since an FE approach only considers the variation within and not between countries, the assessment of whether the models fit the data should be based on the within R^2 score. Looking at this indicator, all models exhibit a relatively high explanatory power and thus fit the data quite well. Even the model with the lowest within R^2 , which is Model 8.25, is able to explain 73.36% of the variations. Since the explanatory power can be assumed to be sufficient, a description of the coefficient estimates can be made in the following.

Focusing first on the determinant that reflects the aggregated amount of subsidies granted for the purchase of PHEVs, the coefficients of this variable exhibit

mixed results across the three groups in regard to the significance of this factor to explain changes in the PHEV registration rate. While the estimate is weakly significant at a 10% level for the regressions of the first two groups, it loses all its significance for the regressions including the ln transformed charging infrastructure variable. Considering the previously mentioned issue of the loss in observations for the regressions in the last group, it could be the case that important sample observations might be missing and therefore the variable turns out to be insignificant. Nevertheless, these results question whether subsidies exhibit the hypothesised significant influence on the PHEV market.

Looking at the second regression of the groups and breaking down subsidies based on whether they are granted once or more frequently, the results indicate that while *One-Time Subsidies* do not significantly influence the PHEV market, *Recurring Subsidies* do. Thereby, the marginal effects of the variable *Recurring Subsidies* is with 0.119% for the most conservative estimates between the groups surprisingly high. The practical interpretation of this coefficient would be, that if a country decides to increase the amount of the recurring incentives for this vehicle type by 1,000 € the registration rate of this vehicle type would grow by 119%. To better illustrate this relationship and using the average of the registration rate as a starting point (1.04%), a 1,000 € increase would lead to a PHEV registration rate of 2.28% ($1.04 \times (1 + 119.9\%)$) if everything else remains the same. Considering that the average amount of recurring subsidies is however rather low with 327 € and only four countries have exceeded the amount of 1,000 € for recurring incentives, it is questionable whether the effect is equally great in magnitude for such large changes in the amount of this subsidy type. For the one-time subsidies, no individual incentive type seems to significantly impact the PHEV market as it can be derived from the results of the third regressions in the respective groups. Indifferent to the regression group, none of the specific one-time subsidies variables exhibits a coefficient that is significant at least at a 10% level.

Continuing with the description of the results, in this part of the investigation the results of an FD approach are also presented. Since the FD approach calculates the difference between two consecutive time periods and uses these values for the determination of the coefficient estimates, the selection of such an approach leads to the loss of the first year of observations. This loss in observations is especially relevant when having only a short time series in the data set as it is the case in this analysis. Consequently, it is assumed that more reliable results are obtained

from the results of the FE models. Thus, only a brief description of the FD results takes place at this stage.

The results for the aggregated *Subsidies* variables of this approach contributes to the discussion whether this factor significantly affects the PHEV market by providing evidence for the insignificance of this determinant. The estimates of this determinant are insignificant for the regressions of each group. However, it should be noted that the same drawback in terms of losses in observations now also applies for all regressions in this model setting. Moreover, the sample size of the first two groups is even smaller than for the regressions of Group 3 with the FE approach. Another interesting observation that should be pointed out at this stage is that the variables *VAT* as well as *Income Tax* exhibit significant coefficients at a 1% level. In addition the sign of the estimates for the variable *Income Tax* is surprisingly negative regardless of whether the charging infrastructure is included in the regression or not. This would mean that an increase in the amount of *Income Tax* subsidies result in a decrease of PHEV sales and is therefore counter intuitive. An explanation for this outcome can be provided when looking at the data set. Based on the calculations performed in this investigation income tax subsidies for PHEVs can only be reported for one country (Luxembourg). Hence, there are not sufficient observations in the sample for this tax that deviate from the value 0, wherefore the estimate for this factor can be considered meaningless. In general this result underscores the limited explanatory power of the results for the individual one-time subsidies.

Table 8.42: Regression Results PHEV Market: Fixed Effects Models

Variable	Group 1			Group 2			Group 3		
	Model 8.19	Model 8.20	Model 8.21	Model 8.22	Model 8.23	Model 8.24	Model 8.25	Model 8.26	Model 8.27
Subsidies	0.0146%* (0.00008)			0.0146%* (0.00008)			0.0120% (0.00008)		
One-Time Subsidies		0.0109% (0.00007)			0.0109% (0.00007)			0.0078% (0.00006)	
Rebate			0.0057% (0.00008)			0.0057% (0.00008)			0.0010% (0.00005)
VAT			0.0085% (0.00006)			0.0083% (0.00006)			0.0083% (0.00007)
POSTax			0.0192% (0.00015)			0.0195% (0.00016)			0.0165% (0.00016)
Income Tax			-0.0135% (0.00009)			-0.0128% (0.00009)			-0.0087% (0.00009)
Recurring Subsidies		0.1201%*** (0.00041)	0.1224%*** (0.00042)		0.1199%*** (0.00041)	0.1212%*** (0.00040)		0.1307%*** (0.00040)	0.1316%*** (0.00039)
LN(Electricity to Diesel Price)	0.238% (0.60357)	-0.101% (0.57630)	-0.220% (0.59168)	0.174% (0.59766)	-0.102% (0.57159)	-0.232% (0.59217)	0.831% (0.50892)	0.533% (0.44053)	0.423% (0.50653)
Trend	2.4E+7%*** (75.773)	2.3E+7%*** (63.307)	2.6E+7%*** (64.767)	3.4E+7%*** (83.494)	2.3E+7%*** (78.366)	2.9E+7%*** (78.509)	2.2E+7%*** (150.15)	1.5E+7%*** (129.70)	1.5E+7%*** (137.07)
Chargers per 100km highway				-0.0358% (0.00058)	-0.0014% (0.00033)	-0.0075% (0.00025)	-0.0981% (0.10957)	-0.0600% (0.10548)	-0.0410% (0.10989)
Observations	264	264	264	264	264	264	243	243	243
F-score	111.72***	139.27***	n.a.	80.79***	151.02***	n.a.	85.70***	116.90***	n.a.
Within R^2	0.7501	0.7722	0.7751	0.7515	0.7722	0.7752	0.7336	0.7707	0.7751
Between R^2	0.0354	0.0590	0.0821	0.0013	0.0572	0.0736	0.0100	0.0151	0.0394
Overall R^2	0.5822	0.5708	0.5733	0.5525	0.5699	0.5692	0.4734	0.4867	0.5105

Note: Country Fixed Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** p < 0.01

** p < 0.05

* p < 0.1

Table 8.43: Regression Results PHEV Market: First Differences Models

Variable	Group 1			Group 2			Group 3		
	Model 8.19	Model 8.20	Model 8.21	Model 8.22	Model 8.23	Model 8.24	Model 8.25	Model 8.26	Model 8.27
Subsidies	0.00072% (0.00006)			0.0071% (0.00006)			0.0095% (0.00006)		
One-Time Subsidies		0.0021% (0.00006)			0.0021% (0.00006)			0.0045% (0.00006)	
Rebate			0.0019% (0.00008)			0.0019% (0.00008)			0.0077% (0.00007)
VAT			0.0211%*** (0.00003)			0.0213%*** (0.00003)			0.0216%*** (0.00002)
POSTax			-0.0064% (0.00015)			-0.0067% (0.00015)			-0.0107% (0.00015)
Income Tax			-0.0333%*** (0.00002)			-0.0311%*** (0.00003)			-0.0299%*** (0.00004)
Recurring Subsidies		0.1061%** (0.00042)	0.1087%** (0.00041)		0.1057%** (0.00042)	0.1083%** (0.00041)		0.1103%** (0.00044)	0.1145%** (0.00043)
LN(Electricity to Diesel Price)	-0.489% (0.63739)	-0.841% (0.65177)	-0.879% (0.67561)	-0.503% (0.66156)	-0.848% (0.66999)	-0.885% (0.69291)	-0.153% (0.70206)	-0.158% (0.69611)	-0.149% (0.70501)
Trend	2.1E+8%*** (102.63)	1.5E+8%*** (102.05)	1.2E+8%*** (111.61)	2.9E+8%*** (123.95)	1.8E+8%*** (122.43)	1.5E+8%*** (130.18)	5.8E+7%*** (145.33)	3.9E+7%*** (140.71)	2.7E+5%*** (157.05)
Chargers per 100km				-0.0346% (0.00033)	-0.0209% (0.00030)	-0.0211% (0.00029)	-0.0243% (0.14638)	-0.0178% (0.14649)	-0.0085% (0.14953)
Observations	231	231	231	231	231	231	212	212	212
F-score	90.57***	77.74***	n.a.	81.67***	71.37***	n.a.	58.92***	62.88***	n.a.
Overall R^2	0.2877	0.3301	0.3376	0.2884	0.3304	0.3378	0.2891	0.3427	0.3566

Note: First Difference model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** $p < 0.01$

** $p < 0.05$

* $p < 0.1$

8.3.5 Robustness Tests

To check for the robustness of the results, the same tests in the same order are performed in this investigation. Thus, in the first robustness test the trend variable is replaced by time dummy variables. Thereafter, two dynamic panel data models in form of a GMM and LSDVC approach are applied to investigate regression models that include lags of the dependent variable. In the final robustness test, the considered time frame of the investigation is reduced to the year 2017 to check for potential changes in the efficiency of the subsidies on the PHEV market.

8.3.5.1 Time Dummies

Following the structure of the EV and BEV investigation, a two-way FE model is executed as a first robustness test. As opposed to the EV and BEV investigation, the statistical software was not able to calculate an F-score value for most of the models in this setting. The reason for this is that for the PHEV market, only one country (Sweden) exhibited PHEV registrations in 2010. Thus, due to the $\ln$ transformation of the dependent variable the 0 registration rate of the other countries became missing observations. Consequently, the time dummy variable of the year 2010 only reflects one observation which prevented the successful calculation of an F-score.

Moving on with the analysis and focusing on the significance and magnitude of the coefficients of the estimates, it can be seen that the aggregated *Subsidies* values do not exhibit a significant influence on the PHEV market. Hence, these model specifications provide support for the presumption that subsidies do not significantly influence the PHEV market, established in the previous chapter. On the contrary, the results of this robustness test confirm the significant influence of *RecurringSubsidies* on the PHEV registration rate. Although this determinant loses in significance and magnitude in either of the models, it is still significant at a 5% level and provides relatively high estimates for all regressions in which it is considered. In line with the results obtained for the EV and BEV investigation, the estimates of the dummy variables are also highly significant and increase in value with proceeding years. Thus, including a trend variable in the main part of the investigation is justified and the results are, based on these tests, robust.

Table 8.44: Regression Results PHEV Market: Fixed Effects with Time Dummies

Variable	Group 1			Group 2			Group 3		
	Model 8.19	Model 8.20	Model 8.21	Model 8.22	Model 8.23	Model 8.24	Model 8.25	Model 8.26	Model 8.27
Subsidies	0.0077% (0.00007)			0.0076% (0.00007)			0.0073% (0.00007)		
One-Time Subsidies		0.0046% (0.00006)			0.0047% (0.00006)			0.0045% (0.00005)	
Rebate			0.0022% (0.00004)			0.0020% (0.00004)			0.0029% (0.00004)
VAT			0.0068% (0.00005)			0.0060% (0.00006)			0.0015% (0.00007)
POSTax			0.0075% (0.00015)			0.0083% (0.00015)			0.0076% (0.00013)
Income Tax			0.0027% (0.00006)			0.0045% (0.00008)			0.0119% (0.00011)
Recurring Subsidies		0.1003%** (0.00039)	0.1002%** (0.00040)		0.0971%** (0.00035)	0.0966%** (0.00035)		0.1042%** (0.00043)	0.1052%** (0.00043)
LN(Electricity to Diesel Price)	0.0433% (0.65416)	-0.2359% (0.60810)	-0.2195% (0.60521)	-0.0748% (0.63973)	-0.2650% (0.60907)	-0.2572% (0.61001)	0.2086% (0.59889)	0.0311% (0.54807)	0.0218% (0.55333)
Chargers per 100km highway				-0.0484% (0.00068)	-0.0159% (0.00043)	-0.0195% (0.00039)	-0.1678% (0.11808)	-0.1401% (0.11565)	-0.1453% (0.12844)
Time Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	264	264	264	264	264	264	243	243	243
F-score	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	57.43***	74.42***	n.a.
Within R^2	0.8425	0.8589	0.8594	0.8450	0.8592	0.8598	0.8124	0.8356	0.8362
Between R^2	0.0285	0.0008	0.0040	0.1425	0.0011	0.0000	0.1491	0.0198	0.0127
Overall R^2	0.6010	0.6089	0.6166	0.5540	0.5955	0.6022	0.4355	0.4752	0.4847

Note: Country Fixed Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** p < 0.01

** p < 0.05

* p < 0.1

8.3.5.2 Dynamic Regression Models

As in the analyses for the EV as well as BEV market, the results obtained in the main part of the investigation are also tested for their robustness by means of dynamic panel data models. Due to a relatively small data set and to avoid instrument proliferation, only the regression models of the groups with the aggregated *Subsidies* determinant are considered. The initial dynamic panel data model that is considered in this part of the analysis is a GMM approach. In particular, a difference GMM approach following Arellano and Bond (1991) is employed, as the obtained estimates for the lagged dependent variable from this approach are well situated between the upper and lower bounds estimates.

In contrast to the previous investigations applying this method, the model that exhibited the best results for the diagnostic tests was not obtained with a model that instrumented one lag of the dependent variable but with a lag length of three. Models that included only one or two lags of the dependent variable exhibited signs of second order correlation and thus should not be considered for the investigation. A major drawback of increasing the lag length is the loss of observations. This is especially a problem if the data set is already small as it increases the probability of small sample bias. The other specifications applied to the GMM model are the same as in the EV and BEV investigation and can be seen in Table 8.45.⁴

Looking first at the results of the diagnostic tests of the regressions, which were already touched upon previously, the regressions do not exhibit any sign of second order serial correlation. Focusing on the p-value of the Hansen J statistic, the results are mixed for the regressions of the different groups. While the p-values for the regressions of the first and third group are neither too high nor low, the probability score of the second regression is relatively high and could therefore be a sign that the model is overspecified. Changing the specifications of the model, however, does not lead to better results. While a decrease of the lag length results in second order serial correlation, an increase of the lag length causes a deterioration of the Hansen J statistic, in form of a higher p-value. Thus, although the results for the second regression reported in Table 8.45 are those of the best possible GMM model, they should nevertheless be interpreted cautiously. Evaluating the significance of the main independent variable, the determinant that was weakly statistically significant in the main part of the investigation turns out to be not statistically significant at all in the GMM approach. This supports the

⁴Different models are presented in Appenix O

previously established assumption that subsidies for PHEVs do not significantly influence the purchase of this vehicle type. Although, the coefficients of variables that are insignificant are usually not interpreted, a brief look at the magnitude of the estimates shows that the FE approach might have over-reported the effect of subsidies on the PHEV market.

Table 8.45: Results PHEV Market: Difference GMM

Variable	Group 1	Group 2	Group 3
L.ln(EV registration share)	0.6585%*** (0.23630)	0.3450%*** (0.15688)	0.6111%*** (0.20100)
Subsidies	0.0030% (0.00005)	0.0032% (0.00005)	0.0039% (0.00006)
LN(Electricity to Diesel Price)	-0.2050% (0.62045)	-0.4064% (0.43157)	-0.1672% (0.59650)
Chargers per 100km		-0.0736%** (0.00028)	-0.0654% (0.21976)
Yearly Time-Dummies	✓	✓	✓
Two-step GMM	✓	✓	✓
Robust	✓	✓	✓
Windmeyer correction	✓	✓	✓
Orthogonal	✓	✓	✓
Observations	141	141	141
F-score	101.43***	107.83***	92.76***
Number of Instruments	17	18	18
Instruments (lags used)	EV (1-3)	EV (1-3)	EV (1-3)
AR(2) probability	0.339	0.559	0.389
Hansen J statistic	0.163	0.263	0.175
FE Lower Bound	0.452	0.398	0.450
OLS Upper Bound	0.629	0.633	0.634

The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** p < 0.01

** p < 0.05

* p < 0.1

As in the investigations of the EV and BEV market, a potential bias arising from the small sample of this analysis could have compromised the reliability of the GMM approach. Moreover, the higher lag length of the dependent variable and the resulting additional losses in observations in this investigation could have amplified this bias. Consequently, an LSDVC panel data model is applied in the following as a second dynamic panel data robustness test. This model seems to be the most appropriate especially in light of a small sample. The LSDVC model is further specified with an Arellano and Bond (1991) bias correction and a bootstrap with 100 repetitions is applied to estimate the variance-covariance matrix.

Table 8.46: Results PHEV Market: LSDVC Models

Variable	Group 1	Group 2	Group 3
L.ln(EV registration share)	0.3434%*** (0.06784)	0.3077%*** (0.06619)	0.3327%*** (0.06441)
Subsidies	0.0044% (0.00003)	0.0037% (0.00003)	0.0039% (0.00003)
LN(Electricity to Diesel Price)	-0.0822% (0.68228)	-0.2689% (0.72048)	-0.0312% (0.68416)
Chargers per 100km		-0.0930%*** (0.00023)	0.0572% (0.10264)
Yearly Time-Dummies	✓	✓	✓
Bias correction	AB estimator	AB estimator	AB estimator
Bootstrap number	100	100	100

The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. AB stands for Arellano and Bond (1991).

*** p < 0.01

** p < 0.05

* p < 0.1

The results of the LSDVC model confirm the findings of the GMM approach and provide insignificant estimates for the *Subsidies* determinant regardless of the group. Thus, based on the results of the dynamic panel data regressions it can be concluded that the PHEV market is not influenced by financial incentives.

8.3.5.3 Limited Time Frame

Following the structure of the analysis of the EV and BEV market, in this part of the robustness analysis it is determined whether the effect of subsidies on the PHEV market has diminished over the last three years. Subsequently, the investigated time frame for the three models spans from 2010 to 2017. The considered models in particular, are the first two model specifications of Group 1 from the main part of the investigation as well as the LSDVC approach alternative of the first model from Group 1 and are reported in Table 8.47. The regression results with the reduced time frame provide interesting new insights in the relationship between subsidies and the PHEV market. Starting with the significance of the variables, in contrast to the results of the main part of the analysis, the main independent variable *Subsidies* turns out to be a significant determinant for the PHEV market in the earlier years. Exhibiting significance at a 1% level in the first two regressions and a significant test result for the variable *One-Time Subsidies* in the third regression, the outcomes provide first evidence for the hypothesis of a diminishing effect of subsidies on the PHEV market over the last years. This hypothesis is further supported when comparing the estimates of the regressions with the different time frames. The coefficients of the main independent variable are all substantially larger for the regressions with the limited time frame than for the regressions

covering the entire investigated time period. The estimated effect of *Subsidies* on the PHEV market for the LSDVC as well as FE models with the aggregated *Subsidies* variable limited to the year 2017 is larger by almost 0.01% compared to their counterparts investigating the effect until 2020.

Table 8.47: Results PHEV Market: Time Frame 2010-2017

Variable	LSDVC	Model 8.19	Model 8.20
L.ln(EV registration share)	0.0218% (0.07744)		
Subsidies	0.0138%*** (0.00005)	0.0239%*** (0.00008)	
One-Time Subsidies			0.0180%** (0.00007)
Recurring Subsidies			0.1639%** (0.00070)
LN(Electricity to Diesel Price)	-0.4059% (1.14583)	-1.5047% (1.09751)	-2.0586%* (1.12158)
Trend		8.4E+8%*** (140.881)	1.1E+9%*** (141.702)
Yearly Time-Dummies	✓		
Bias correction	AB estimator		
Bootstrap number	100		
Observations		177	277
F-score		78.42***	54.22***
Within R^2		0.6966	0.7233
Between R^2		0.0179	0.0445
Overall R^2		0.4103	0.3867

The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. AB stands for Arellano and Bond (1991).

*** $p < 0.01$

** $p < 0.05$

* $p < 0.1$

8.4 A Comparison of the Effect Size of Subsidies Depending on Vehicle Type

While in the previous investigation differences in the effect size of subsidies on the different vehicle types have already been frequently touched upon, this part of the analysis is particularly dedicated to showing and discussing these differences. Hence, in this section the established hypothesis in the literature review that subsidies influence the vehicle types differently is dealt with. Trying to simplify the description of differences in the significance and size effects of subsidies on the respective vehicle types, Table 8.48 is prepared. In this table the coefficients of the determinants approximated for the vehicle types from the corresponding chapters are presented. In particular, to prevent the table from becoming too complex, only the regression results of Group 2 are reported. The results of Group 2 are considered to be representative for each vehicle type, as they include the possible important charging infrastructure determinant but do not suffer from observation loss because of an $\ln$ transformation of this variable. Moreover, the Ramsey RESET test indicated that this group of regressions is correctly specified for the EV and PHEV investigation. Only in the analysis for the BEV market the models of the second group exhibited signs for a possible misspecification. However, when comparing the results to the estimates of the models from group 3, which was the only group that was correctly specified, they are quite similar in terms of significance and magnitude of the coefficients. Only the variable *Recurring Incentives* exhibited estimates on a lower significance level, which nevertheless were still significant at a 10% and 5% level, in the two regressions where this determinant was considered. Consequently, since the coefficients of these two groups are relatively similar in the BEV investigation, using the results of Group 2 should allow the investigation of differences between vehicle types. In addition to the FE regression results, the results obtained for the second group with the LSDVC approach are reported in the lower part of Table 8.48. Since this approach was only applied to the model with the aggregated amount of subsidies for each vehicle type, no results can be reported for the *Subsidies* determinant on a more detailed level.

Comparing the estimates obtained for the regressions of the BEV as well as PHEV market with those of the accumulated EV market (Table 8.48), it can be observed that the coefficients of the main independent variables are generally

8.4. A COMPARISON OF THE EFFECT SIZE OF SUBSIDIES DEPENDING ON VEHICLE TYPE

smaller for the BEV market regressions and larger for the PHEV market regressions. Starting with the aggregated *Subsidies* variable an interesting observation is that while the coefficients of this determinant are highly significant for the investigation of the accumulated EV and the BEV market the significance of subsidies are questionable for the PHEV market. The estimate is only significant at a 10% level for the FE regression in the second group of regressions as reported in Table 8.48. However, the results of the third group of regressions, which is not reported in this chapter but can be found in Table 8.27, and the LSDVC approach suggest no significant influence stemming from this variable on the PHEV market. An insignificant influence of subsidies on the PHEV registration rate and in contrast a significant influence on BEV registration is, however in line with the findings of Narassimhan and Johnson (2018). In this research it is hypothesised that the insignificant influence of subsidies on the PHEV market could be explained by the less significant behavioral changes the switch from an ICC to this vehicle type requires. Customers of PHEVs do not have to adjust as strongly to a new refuelling behavior as customers of a BEV need to. Therefore, it could be the case that they do not require as many financial incentives. Hence, support for the hypothesis that subsidies affect the adoption of the vehicle types differently is already provided with this result.

Breaking down subsidies based on recurrence and distinguishing between one-time and recurring subsidies the insignificant influence of subsidies on the PHEV market could also be explained with the insignificant influence one-time subsidies have on the PHEV market. As the results show, while both one-time and recurring incentives are significant determinants for the EV and BEV market, one-time subsidies do not play an important role for the development of the PHEV market. A potential explanation, therefore, could be the insufficient or lack of rebates that are granted for PHEVs. When comparing Figure 8.6 with Figure 8.10, it can be seen that rebates are more often granted for BEVs and are also commonly higher in magnitude. This assumption is further supported by the significant *Rebate* coefficient that is obtained for BEVs and EVs and not for PHEVs. A discussion of differences between other one-time subsidies will not take place because of the impaired explanatory power of the estimates due to the limited number of observations. However, another important group of subsidies that has already been mentioned and should be looked at more closely is *Recurring Subsidies*. Recurring Subsidies are the only financial incentives, which exhibit a significant coefficient

for both the BEV and PHEV market and also in the aggregated EV regression. In terms of significance, there is no large difference in the estimates between the regressions of the markets. While *Recurring Subsidies* are significant at a 5% level for the EV and BEV analysis, the variable exhibits significant results at a 1% level for the PHEV analysis. A noticeable difference between the markets is however the magnitude of the calculated influence. Especially the coefficients of the *Recurring Subsidies* variable are substantially smaller in the BEV analysis when comparing them to their EV and in particular PHEV counterparts. This would imply that due to the stronger impact of *Recurring Subsidies* on the PHEV market, the actual impact of an increase in the amount of subsidies on the BEV market is smaller than the results of the EV investigation suggest. Hence, this outcome emphasises the additional value a distinction between the BEV and PHEV market entails.

For the control variables, based on the reported results in Table 8.48 an insignificant influence of the fuel price ratio on all markets can be concluded. Although, the coefficient is significant at a 10% level for the aggregated EV analysis, when relying on the estimates of the FE approach, the results of the LSDVC approach refute the significance of this determinant even for the EV market. A more interesting observation can be made when looking at the estimates for the charging infrastructure determinant. This factor seems to be significant only for the EV analysis. When also considering the LSDVC analysis, the charging infrastructure determinant also becomes a driver of the PHEV market. The coefficients, however, exhibit a not anticipated negative sign just like in the EA or innovativeness analyses from this dissertation.

In conclusion, the differences in significance as well as magnitude of the influence for the different types of subsidies on the markets provide evidence for the hypothesis that consumers of BEVs and PHEVs are inclined by different subsidy types to engage in their purchase behavior.

Table 8.48: Fixed Effects Regression Results

Variable	EV			BEV			PHEV		
	Model 8.4	Model 8.5	Model 8.6	Model 8.13	Model 8.14	Model 8.15	Model 8.22	Model 8.23	Model 8.24
Group 2									
Subsidies	0.0076%*** (0.00002)			0.0060%*** (0.00002)			0.0146%* (0.00008)		
One-Time Subsidies		0.0066%** (0.00003)			0.0056%** (0.00002)			0.0109% (0.00007)	
Rebate			0.0068%** (0.00003)			0.0073%*** (0.00002)			0.0057% (0.00008)
VAT			0.0015% (0.00009)			-0.0019% (0.00008)			0.0083% (0.00006)
POSTax			0.0082%* (0.00005)			-0.0011% (0.00008)			0.0195% (0.00016)
Income Tax			-0.0044% (0.00007)			-0.0021% (0.00002)			-0.0128% (0.00009)
Recurring Subsidies		0.0225%** (0.00011)	0.0242%** (0.00012)		0.0087%*** (0.00002)	0.0096%*** (0.00002)		0.1199%*** (0.00041)	0.1212%*** (0.00040)
LN(Electricity to Diesel Price)	-1.069%* (0.57596)	-1.132%* (0.57351)	-1.166%* (0.58716)	-0.761% (0.64191)	-0.783% (0.64661)	-0.754% (0.65194)	0.174% (0.59766)	-0.102% (0.57159)	-0.232% (0.59217)
Trend	7.1E+6%*** (54.781)	6.9E+6%*** (56.341)	7.3E+6%*** (60.798)	1.6E+6%*** (52.418)	1.7E+6%*** (52.907)	1.5E+6%*** (52.101)	3.4E+7%*** (83.494)	2.3E+7%*** (78.366)	2.9E+7%*** (78.509)
Chargers per 100km highway	-0.0486%*** (0.00011)	-0.0456%*** (0.00012)	-0.0455%*** (0.00015)	-0.0168% (0.00030)	-0.0164% (0.00029)	-0.0010% (0.00029)	-0.0358% (0.00058)	-0.0014% (0.00033)	-0.0075% (0.00025)
LSDVC									
	(EV)			(BEV)			(PHEV)		
LN(EV registration share)	0.4221%*** (0.06643)			0.4056%*** (0.06486)			0.3077%*** (0.06619)		
Subsidies	0.0066%*** (0.00002)			0.0057%*** (0.00002)			0.0037% (0.00003)		
LN(Electricity to Diesel Price)	-0.4598% (0.42045)			-0.3024% (0.43171)			-0.2689% (0.72048)		
Chargers per 100km highway	-0.0434%** (0.00018)			-0.0167% (0.00018)			-0.0930%*** (0.00023)		

Note: Country Fixed Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** p < 0.01

** p < 0.05

* p < 0.1

8.5 Discussion of Results

The results obtained in this part of the dissertation confirm the findings of previous research but also contribute to this research stream in various ways. In general this work can be seen as an extension of Münzel et al. (2019), wherefore references are often made to the findings of this study in particular. To be precise, it should complement their study by analysing whether subsidies are still a significant determinant when considering the last three years, differentiating between vehicle types, testing for a potential overestimation of the influence of subsidies on the market as well as finding out whether the size effect of subsidies has diminished in recent years. First of all, proof for the general research hypothesis that monetary subsidies influence the adoption of EVs is found and is therefore in line with the majority of the studies looking at the EV market in general (Sierzechula et al., 2014; Jenn et al., 2018; Münzel et al., 2019). With approximated marginal effects of about 0.0076%, the results are relatively close to the estimates obtained by Münzel et al. (2019). Differences in the estimates to the study of Münzel et al. (2019) can be explained by small deviations in the calculation of the subsidies, the fact that only 29 instead of 32 countries are considered in this analysis as well as the extended time horizon. Building on the last point, the difference in the estimates can also be evaluated as a first indication for changing influences of subsidies on the EV market depending on the investigated time period. However, an increasing effect for subsidies is counter intuitive to the hypothesis developed in the literature review, as with approaching price parity with ICCs the influence of subsidies was assumed to decrease. Due to differences in the estimation, a comparison of the results with those of Münzel et al. (2019) that can solely be based on the time period is not 100% possible and therefore other tests were executed which will be discussed shortly. It should further be noted that the results for the aggregated *Subsidies* determinant in this study are at a higher level significant than in the study of Münzel et al. (2019). Hence, an extension of the time period and the accompanying greater sample size has lead to more robust standard errors of this determinant, as assumed by the authors.

The results from the investigation of the influence of subsidies on a more detailed level, which was done by dividing them into one-time and recurring incentives, yielded the same observations as in Münzel et al. (2019). Both incentive types are significant but recurring incentives exhibit a much stronger influence on

the EV market than one-time subsidies. The interpretation of the results for the recurring subsidies turns out to be more difficult and limited than for the one-time subsidies, as the outcome depends even more on the calculation approach than for the one-time subsidies. In particular, the problem with recurring incentives is that they are theoretically granted annually and therefore next to other factors depend on the holding period of the vehicle. Since in this investigation the same data collection method as in Münzel et al. (2019) was applied and therefore the holding period is reduced to one year, the perceived financial incentives by an individual could be much larger. This would in turn reduce the size effect of the determinant. However, as consumers discount future earnings that they would receive with a purchase of an EV, the actual impact of this determinant might not be far off the approximated influence (Greene et al., 2005). Going on step further and looking at the individual one time subsidies, based on the results it is certain to conclude that rebates as well as the taxes granted at the point of sales impact the EV market. On the contrary, due to limited observations this assumption is not supported for incentives granted on VAT or income tax.

In contrast to Münzel et al. (2019) an alley of research that has opened up due to improved data availability, is the investigation of subsidies on the individual BEV and PHEV markets. Distinguishing between BEVs and PHEVs, in this investigation allowed to make other interesting observations as discussed in Chapter 8.4. Most importantly, substantial differences in the significance of subsidies in general on the markets were uncovered. In contrast to BEVs, the results of the analysis indicate no influence of the accumulated subsidies on the PHEV market. This finding is in line with the study of Narassimhan and Johnson (2018) and suggests that the purchase of a PHEV is more strongly influenced by other behavioral motives. A possible explanation for this outcome is that the switch to PHEV might not pose such a great behavioral change, wherefore incentives are not as important. Narassimhan and Johnson (2018) assumes that the price difference between a PHEV and comparable ICC is not as large as those of a BEV and its ICC counterpart. Hence, rebates or tax credits are not that important to PHEV customers for reaching price parity. Looking at the purchasing prices of the selected PHEV and its ICC counterpart in this study, this claim cannot be supported as those vehicles exhibited a substantial difference in purchasing price. The PHEV was more than 50% more expensive than the internal combustion car. As explained previously, in this research it is therefore hypothesised that the insignificant influence of subsi-

dies on the PHEV market could be caused due to the less significant behavioral changes required when switching from an ICC to this vehicle type. The adjustment to the fuelling behavior is far less pronounced compared to BEVs. Therefore, it could be the case that PHEV customers do not require as many financial incentives to be enticed to purchase this vehicle type.

While comparing the estimates of the BEV regressions with those of the EV investigation, it became evident that the influence of subsidies is not as high as the EV results might suggest. The larger estimates for the EV analysis are a result of merging BEV and PHEV subsidies and registration rates. As discussed, the estimates for the subsidies for the PHEV market are higher than for the BEV market. Hence merging the values, leads to an estimate that provides information on how the BEV and PHEV market on average react to changes in subsidies but in cases where the vehicle types react differently, the influence of subsidies for the individual vehicle type cannot be derived. Hence, the results presented in this part of the study suggest that no conclusive interpretation of subsidies from an investigation that analysed the influence of subsidies on the aggregated EV market can be made. Therefore, this investigation provides new insights on the true effect size and indicated that interpretations of the findings for the aggregated EV market for one vehicle type in particular need to be made with caution. This becomes, especially a problem when types of subsidies only influence one market. For the aggregated subsidies determinant for example it has been concluded that they do not significantly influence the PHEV market. Hence the first mistake in executing an analysis of the general EV market would be to conclude that the accumulated amount of subsidies influence the PHEV market as well. The second downside of only relying on a general EV market analysis is, that by considering the PHEV data the influence of subsidies on the BEV market would be due to overestimation of the coefficients, interpreted as greater than it actually is. Also, in cases when the subsidy type is significant for both vehicle types, a large difference could lead to imperfect policy development. An example for this are the outcomes obtained for recurring incentives. While the calculated marginal effects of about 0.0087% for BEVs seem more conservative, the influence of this subsidy is with about 0.1199% far higher evaluated for PHEVs. Thus, the estimate of about 0.0225% for the EV regressions would lead to an over-interpretation of the importance of this subsidy for the BEV market and an under-interpretation for the PHEV market.

Building on the point of an overestimation, another contribution in this stream

of literature for studies focusing on subsidies in the European region is the consideration of a natural diffusion of this technology. As pointed out in the literature review, several researchers claim that neglecting the natural diffusion of this new technology would lead to an overestimation of the effect subsidies have on the EV market. Hence, they argue that the inclusion of a lagged dependent variable to account for this development is essential. In this investigation support for this hypothesis is found by not only applying a difference GMM, which is the predominantly applied statistical dynamic panel data method in this stream of research (Jenn et al., 2013, 2018; Narassimhan and Johnson, 2018) but also another instrumental variable approach in form of an LSDVC. The latter approach is favoured in this analysis due to its superior abilities of coping with a small sample. Including the lag of the dependent variable and therefore accounting for network externalities has shown that when neglecting this factor, the likelihood is relatively high that the influence of subsidies on the EV market is overestimated. The results have shown that the FE approach overestimated the influence of subsidies of up to 0.0015% (Model 1 of Group 1). Moreover, the LSDVC approach confirms the finding of an insignificant relationship between the aggregated *Subsidies* variables and the PHEV market. Only for the BEV market, the inclusion of a lagged dependent variable did not provide evidence for a too severe overestimation of subsidies. Nevertheless, the difference can be considered as substantial, especially when comparing the results of the LSDVC regressions to the, in terms of applied control variables, closely related time dummies regressions. Consequently, the findings of this study support the recommendations made by previous research (Jenn et al., 2013, 2018; Narassimhan and Johnson, 2018) to include a lagged dependent variable, especially for investigations that do not only want to determine the significance of a factor but focus on determining the marginal effects of the determinant.

As mentioned in the beginning of this section, another contribution this paper was aiming to make is to provide evidence for the decreasing influence of subsidies on the EV market. For this purpose robustness tests were performed that limited the investigated time frame to the year 2017. In general the higher marginal effects of this investigation compared to those considering the entire time period indicate that indeed the effect of subsidies was higher in the earlier years of the market for EVs and PHEVs. In case of the PHEV market the estimates of the aggregated subsidies determinant even turns out to be significant at a 1% level. Mixed results for the BEV analysis are, however, not as clear as those of the EV

and PHEV analysis. Marginally higher estimates from the FE regressions for the time period 2010 to 2017 do not clearly provide proof that the influence of subsidies has decreased over time, while on the contrary substantially greater estimates obtained with the LSDVC approach support this assumption. Since, it is assumed that estimates obtained with the LSDVC approach are more accurate than those with the FE approach, a diminishing influence of subsidies on the BEV market can also be concluded. A potential explanation for the diminishing influence of subsidies on the vehicle market is that as technologies are advancing the product is becoming cheaper. Thus less financial incentives are required to convince people to purchase the product as the price of the innovation approximates parity with the product it is supposed to replace. Moreover, the technologies become better than the product they are trying to replace, hence according to Rogers (2003), the product will witness a natural diffusion and sell itself.

Based on the findings of the analysis various implications for policy makers can be derived. First of all, due to the positive influence of subsidies on the general EV market, this policy measure presents a good mechanism of how governments can influence the purchase behavior of the citizens and companies within a country. Thus, governments should grant subsidies as they increase the general EV registration rate in the range of 7.4% to 7.8% per additional 1,000 €. The strategy in terms of which specific subsidies are granted should vary depending on vehicle type. While the purchase of BEVs should be supported with one-time subsidies such as rebates, a government should focus more strongly on recurring subsidies to foster the development of the PHEV market. When recalling that subsidies are a policy measure the primary goal of which is to reduce price differences between EVs and ICCs, a decrease in the magnitude of the influence as well as significance also allows the establishment of other interesting implications. The decreasing influence of subsidies on the EV market might be an indicator that the financial differences between EVs and ICCs are becoming less of a problem as they approach price parity. Hence, even a reduction of subsidies might seem possible when a natural diffusion of the technology takes place, especially in those countries with a wealthy population. This should however not mean that the money should not be used to foster the EV market, but a possible idea could be to allocate the resources to an international fund, poorer countries can use to subsidise the EV market in their country. As found out by Rietmann and Lieven (2019), poorer countries issue less subsidies for the purchase of such a vehicle, as they are exposed to limited financial resources.

With the establishment of such funds, governments of poorer countries do not have to wait until the prices of EVs have significantly decreased and a larger secondary market has developed. The quick development of the EV market can be assumed to be of interest for the sponsor countries of such a fund as well, since as pointed out in Chapter 7, climate change is a global problem and therefore a transition to a sustainable transportation mode has to take place in as many countries as quickly as possible. In case the countries do not want to engage in philanthropy, another idea of structuring such a fund is to make the money available to the countries in form of debt with a low interest rate. The establishment of international funds to overcome global problems is not unprecedented. One example is the utilisation of the European Stability Mechanism to combat the issues arising from the recent Corona Virus (European Stability Mechanism, 2021).

As in the analyses of the influence of EA and innovativeness on the EV market, this study is also not free of limitations. Most of the limitations in this study are concerned with the methodological approach on which the calculation of the subsidies is based. As discussed in Chapter 4, in this study subsidies are defined to be any monetary incentives a customer directly receives from the purchase of an EV or indirectly profits from because of preferential treatments in the calculation of taxes in comparison to a comparable ICC. These preferential treatments can either take on the form of an explicit reduction or exemption from a tax or a lower tax burden in cases where a tax is based on CO_2 emissions. To determine the subsidy amount a customer of an EV receives, a vehicle pair for BEV and PHEV with an ICC counterpart had to be selected, as a subsidy is only considered to be an incentive if the payable tax is lower for the EV than for a comparable ICC. Hence, the first assumption that needed to be made is how customers perceive subsidies. Potential customers of EVs might not compare the advantages of taxes with a comparable ICC but rather look at the difference between the tax amount with and without incentive and consider the difference as a saving. When comparing the costs of the vehicle with incentives to its original price and using this value as the subsidy amount, the issue arises on how to quantify the savings customers receive if the tax is based on CO_2 emissions. In this case an EV clearly has an advantage over an ICC and the purchase of such a vehicle is incentivised but a calculation of the subsidy amount is not possible as no reference value for CO_2 emissions exists. The approach applied in this study is in line with previous research (Sierzechula et al., 2012; Münzel et al., 2019) and provides advantages in terms of consistency

in the calculation of subsidies. Another issue of this approach is, however, that the calculation of the subsidies amount depends on the selection of the vehicle pairs. Consequently, an assumption had to be made what kind of vehicle an EV customer would have purchased instead. Since this is objectively not possible, a possible approach is to look at ICCs with comparable car attributes like performance criteria. In addition, since differences in car attributes as well as price are often considered in the calculation of taxes, the selection of the car models presents to be an important factor that determines the calculated amount of subsidies. It therefore had to be decided, which vehicles can represent the BEV and PHEV market respectively, and what can be considered a comparable ICC. As argued in the Data chapter, to avoid subjective influences and ensure comparability of the findings, the same car models are selected in this study as in Münzel et al. (2019). The authors argue the appropriateness of the considered models by the high market share of these cars in the early years of the market, wherefore they can be considered as representative for the entire market. Moreover, to prevent an upward bias of the results, the selection of the car models in terms of price is also conservative. Nevertheless, it should be noted that deviations in the calculated and real subsidies exist as the final amount of subsidies a customer receives depends on its ultimate vehicle choice. Adapting the same methodology for incentive calculation as in Sierzechula et al. (2014) and Münzel et al. (2019), entailed also other limitations which have been explained in detail by Münzel et al. (2019). These encompass limitations such as an equal weighting of subsidies for corporate as well as private consumers in the calculation of subsidies or the assumption that consumers are aware of the subsidies and also claim them. Another prerequisite that is in conjunction with the latter point is that car dealerships pass the incentives down to the customers. If this is not the case, the estimate obtained in this study might slightly over-report the effect size of subsidies on the respective EV markets. A further and more detailed discussion and justification why these limitations should not exhibit a too severe influence on this research can be found in Münzel et al. (2019).

Besides the potential problems that might arise from the calculation of the subsidy amount, another limitation of this study is that it only considers the influence of incentives on country level. Hence, differences that exist on regional level within a country are not considered, wherefore the estimates of the influence of variables might be slightly biased. This limitation is, however, caused by the geographic scope of analysis. As this study considers a larger geographic scope,

registration rates of EVs as well as subsidy amounts are difficult to collect or might not even be available at all for such a detailed level (Münzel et al., 2019). Another result of the geographic scope of this research is that non-monetary incentives were also not included in this investigation. This type of subsidies is also often granted on regional level and thus varies within a country. Hence, due to possible correlations with financial incentives, the omission of such factors might have positively biased the results of the regressions.

Derived from the limitations of this study as well as the gap of literature this research could not fill, different recommendations for future research can be made as well. As this study focuses on the subsidies the citizens as well as companies receive for the purchase of an EV and therefore reflect the demand side of subsidies, a quantitative analysis of the influence of subsidies on the EV market from a supply side perspective might provide interesting insights as well. Another recommendation for future research is to analyse whether the influence of subsidies differs based on the model segment of a car such as sports cars, SUVs or compact cars. Previous research has already determined that the influence of subsidies might differ depending on the the car model. For example, Zhang et al. (2016b) found out that for luxury cars incentives might not be as important as for compact cars, since it is hypothesised that the customers purchase such a car as a status symbol and do not rely on the granted subsidies. Moreover, in several countries subsidies such as rebates do not apply to cars when they exceed a certain price threshold. For a research context, this would imply that registration data for the individual vehicle types of the countries is required. Hence, such a research becomes feasible with an improvement of data availability. Lastly, the influence of subsidies on the EV market should frequently be monitored, as found out in the analysis, the influence of subsidies on this market might change over time. Moreover, with progressing time more observations will be available providing the opportunity to enlarge the data set. Hence, it is recommended to repeat this study in the future as more robust estimates can be expected.

8.6 Conclusion

Applying an FE regression approach and therefore controlling for between country differences, the influence of subsidies on the registration rate of the general EV market as well as the BEV and PHEV market in particular has been analysed in

this part of the doctoral thesis. Thereby, the different hypotheses established in Chapter 3.5.2 of the literature review were empirically tested and proof for each provided. Building on the research of Münzel et al. (2019), an extension of the investigated time period by 3 years, which entailed a substantial enlargement of the data set as a positive side effect, has proven that subsidies still significantly influence the general EV market. As additional contributions, distinguishing between the BEV and PHEV market, the analysis in this investigation provides evidence of significant difference in the influence of subsidies on the respective registration rates. While it is found that subsidies significantly influence the BEV market, the results of the analysis indicate an insignificant relationship between subsidies and the PHEV market, questioning whether granting subsidies for the purchase of PHEVs still makes sense. Including a lagged dependent variable into the regression and hence altering the statistical approach by employing an LSDVC instead of an FE model, this research also accounted for the natural diffusion of these vehicle types in the market. Based on the results, the presumed overestimation of the effect of incentives when applying an FE approach was validated. The last research question that has been analysed in this research setting was whether subsidies lose in importance over the years, as EVs are approaching price parity with ICCs. Limiting the time frame of the investigation until 2017 this hypothesis found support especially for PHEVs, as the determinant turned out to be highly significant when reducing the time frame. In conclusion, the findings of this investigation can be considered as an extension of the work of Münzel et al. (2019) and contribute to the understanding how subsidies influence the EV as well as the BEV and PHEV market.

CONCLUSION

In this chapter, which presents the conclusion of this doctoral thesis, both the key findings of the investigations are reflected as well as directions for future research are presented. This thesis started with an introduction that highlighted the immediate threat climate change poses to the world and introduced EVs as a potential sustainable solution to mitigate CO_2 emissions in the transportation sector. Focusing on the drivers of this market, in the course of the literature review it was identified that, although a multitude of research exists that analysed the determinants of this market on an individual level, a lack of research employing a quantitative approach by using actual market data can be noticed. Studies, investigating determinants from a market perspective however do not only contribute to this stream of research by providing new insights on how a determinant could influence the EV market. They are also essential to validate the findings of the studies on individual level due to potential biases that might have arisen from the attitude-action gap. Taking on a macroeconomic perspective by using actual market data for 29 countries in the EU and EFTA, in this doctoral dissertation the influence of three determinants in particular are investigated, namely *environmental awareness*, *innovativeness* and *subsidies*. The first two factors can be categorised as psychological determinants and are only scarcely if not at all investigated by previous research employing market data. While EA can be seen as an altruistic determinant, innovativeness is considered to be a more self-centered driver of the market in this dissertation. A high explanatory power for the adoption intention

of EVs was assigned to both determinants in extant literature. The influence of subsidies on the EV market on the other hand, is already a well developed research field on macroeconomic level. Nevertheless, limitations of previous research opened up different research gaps that this dissertation addresses. Hence, this doctoral dissertation contributes in general to the understanding of the influencing factors of the EV market. In the following, the key findings of the three chapters dealing with the influences of the three determinants on the EV market are summarised and synthesised. A more detailed discussion of the findings can be found in the discussion of the results as well as conclusions of the respective chapters. Moreover, recommendations for future research are outlined in the subsequent part of this chapter.

9.1 Summary of Results

As mentioned above this doctoral dissertation focuses on determining the influence of the factors *EA*, *innovativeness* and *subsidies* on the EV market. Starting with the altruistic factor EA, that is investigated in Chapter 6, a requirement to be able to analyse this determinant on a macroeconomic level was to find an appropriate measurement that allowed to deduce the society's level of EA. The introduction of a new measurement of EA in form of a Twitter keyword analysis to this stream of literature, is considered in this study as an appropriate tool as the analysis of the frequency of posts containing specific keywords does not only provide information about what information people receive but also what topics they are actively communicating about and therefore which topic is of interest. The results of the investigation revealed that, contradictory to what previous literature focusing on adoption intention has found as well as theory suggests, EA does not significantly influence the EV market. This finding was further supported by employing another measurement of EA in form of a Google Trends analysis. It is hypothesised that other factors pose a too strong market barrier so that this determinant does not play a significant role in the development of this market at least for the investigated time period. This explanation would also be in accordance with the TPB and explain the difference between this study and previous research focusing on adoption intention. According to the TPB, market barriers such as affordability of this vehicle type do not only influence the attitude of an individual and therefore indirectly the final behavior through the behavioral intention but also directly the behavior

itself. Hence, such factors can be categorised into the perceived behavioral control dimension and might prevent a factor from becoming significant for the adoption of this product, although it exhibits a significant influence on an individual's intention. Consequently, the results of Chapter 6 can be seen as further evidence for the attitude-action gap in the EV market. Different implications can be derived from the findings for politics as well as car manufacturers, whereby most of them strongly focus on the communication of politics and practitioners. Amongst others, it is recommended to communicate that several market barriers have already been overcome or are not as strong as often still believed. Moreover, manufacturers of EVs should appeal more strongly to other psychological traits of individuals in the advertisements of these cars.

Based on the insignificant influence of EA, the question arose whether a more self-centered psychological determinant is able to overcome the barriers of the market and exhibit a significant influence on EV registration rates. This self-centered determinant is reflected by innovativeness and its influence analysed in Chapter 7. Similar to the investigation of EA, a lack of research is uncovered that deals with this determinant on a macro economic level. Moreover, the analysis in this dissertation appears to be the first to employ actual market data. To analyse the significance of this determinant, different statistical approaches are executed, that do not only consider the variation of the variables within a group but also between groups. This decision was based on the fact that country innovativeness is a sluggish variable. Thus, the limited efficiency of within estimators would too quickly lead to the assumption of an insignificant influence of this determinant. Employing RE as well as two mixed effects models, the application of which are novel in this research field, yielded significant results for this determinant. Hence, in contrast to the results of the previous investigation, country innovativeness turns out to be a significant determinant for the development of the EV market. The findings of this research are therefore in line with those of the studies dealing with this determinant on individual level. Changing the scope to country innovativeness does not only confirm the findings of studies on individual level but also suggests that an innovative environment might be important as well. Going one step further in the analysis, the results in this chapter have also provided evidence that innovativeness plays a mediating role between wealth and EV registration rate. It therefore, explicitly contributes to the research stream that tries to identify the characteristics of innovative countries or individuals, which is based on Rogers

(1962) DOI theory. This result suggests that the wealth of a country and its citizens influences its level of innovativeness and thus indirectly the adoption of EVs. The implications that can be deduced from this investigation are that in general, policies and actions should be taken that aim to better communicate, improve car attributes or create an environment to experience the five key characteristics of innovations, namely *relative advantage*, *compatibility*, *complexity*, *trialability* and *observability* discovered by Rogers (2003) for EVs. Considering the results from the part of the mediation analysis, especially in poorer countries advantages of EVs must be better communicated and risks reduced, as the population in these countries is not able and less willing to take on greater risks. Another more general implication that can be based on the results is that country innovativeness is a factor to consider for a company developing a new technology in the high-cost segment, when deciding where to launch the product first.

Uncovering that while the psychological determinant innovativeness exhibits a significant influence on the EV market but EA does not, the question arises on how this factor could also become an important driver of this market. As previously hypothesised, the reason why EA is not a significant determinant of this market is because of the several market barriers that prevent the adoption of an EV. Thus, some of these market barriers need to be overcome so that not only innovativeness but also EA becomes a decisive factor of this market. Considered to be one of the biggest market barriers that hinders the adoption of an EV are the relatively high purchasing prices in comparison to ICCs. To counteract these large price differences governments of a multitude of countries grant subsidies for the purchase of EVs. Hence, finally, in Chapter 8 the influence of subsidies on the general EV market as well as the individual BEV and PHEV market is investigated. The analysis of this research question can be seen as an extension of the work of Münzel et al. (2019), as it builds on this study and supplements in different ways the limited quantitative investigations that focus on the European region. First of all, in this study the time horizon is expanded by three additional years (2018, 2019, 2020), which can be seen as substantial when considering the short time period this vehicle type has been present on the mainstream market, and tests whether the significant relationship between subsidies and the EV market still holds. Confirming the significance of this determinant and evaluating the marginal influence with about 6.65% increase in registration rate if the amount of subsidies are increased by 1,000 €, this study further contributes to this stream of research by distinguishing between BEVs and

PHEVs. In doing so, the results of the analysis indicate that while the BEV market is significantly impacted by subsidies, the PHEV market is not. Only when breaking the types of subsidies further down based on whether they are granted frequently or just one time, a significant influence of recurring subsidies can be detected for the PHEV market. This outcome questions the effectiveness and usefulness of subsidies for PHEVs. Diverging from the methodological approach of Münzel et al. (2019), this investigation also supplements their study by applying an LSDVC approach because of the inclusion of a lagged dependent variable. Obtaining smaller coefficients for the *Subsidies* determinant, the assumption for the requirement to account for the natural growth of this technology has been verified as otherwise the influence of subsidies would be over-reported. This is especially important when the research is focused on not only analysing whether a factor is significant but also to determining its marginal effects. Altering the investigated time period to 2017 and comparing the size of the coefficients, it has also been found out that the influence of subsidies on the respective markets diminishes over time. The results of the analysis, especially indicate a decreasing influence of subsidies on the PHEV market. This diminishing influence is assumed to be caused by the decreasing prices of EVs. Due to advancements in research and development EVs are approaching price parity with ICCs, reducing the market barrier of the substantially higher purchasing prices. Hence, subsidies as a policy to bridge the price gap between these vehicle types loses in importance. The results obtained in this chapter are of importance for policy makers to develop policies that can be used to foster the EV market.

9.2 Future Research and Outlook

Recommendations for future research that could address the limitations of this study but also open up completely new avenues for research have been outlined throughout this thesis. Although, this field of research is evolving quickly the actual impact for several determinants is not ultimately determined. With improving market data availability, the investigation of determinants becomes possible which previously only were able to be analysed by means of surveys in the context of adoption intention. Hence, conclusions about the actual impact of these determinants on the market can be derived and researchers do not need to rely on the assumption that purchase intention leads to the eventual purchase behavior. A general

recommendation for future research is also trying to investigate the influence of different psychological determinants on the EV market. As illustrated by the different theories discussed in the literature review, the purchase of a car can be strongly influenced by emotions and is not entirely driven by rational choices. Consequently, despite what previous research focusing on adoption intention suggests, performing analyses with actual market data could also lead to differences in the significance of determinants of this category. Furthermore, as no 100% objective measurement for psychological factors exist, different and innovative measures that can be used as a surrogate for a psychological determinant should be applied. Building on this point, in this study it is encouraged to check the validity of the results from the chapters focusing on the two psychological determinants by using new methods to measure EA and innovativeness. In general, in this stream of research it can be suggested to frequently repeat studies and see whether the relationships between the determinants and the EV market still hold. This is important as the market is evolving quickly and societal issues are constantly evolving. Lastly, in this thesis the influence of determinants was only assessed for EVs that are either entirely driven by electricity or incorporate an electric motor, which can be charged via the electric grid, next to an internal combustion motor. Hence, cars that are powered by hydrogen are neglected in this research, although they are considered to be a potential solution for a more sustainable transportation mode as well. Determining the drivers of this market will however be left to another doctoral student. In conclusion, it is important to extend the research in this field, as it is not unlikely that the findings of this market are transferable to other products in the higher price segments. Hence, corporations as well as governments can use these findings to develop strategies to accelerate the adoption of sustainable innovations.

Despite the need for future research, overall the findings of this doctoral thesis make a valuable contribution to understanding what drives the EV market. As outlined in the beginning of this thesis, it is critical for today's society to find ways to mitigate CO_2 emissions and therefore counteract the negative development of climate change. Learning about drivers of environmentally sustainable innovations is an important part of understanding and supporting this transition and therefore research in this field is critical and of utmost importance.



ENVIRONMENTAL AWARENESS: DIAGNOSTIC TESTS

The following tables present the results of the Hausman (1978) tests of Chapter 6. Based on the two different measures that have been applied to analyse the influence of EA on EV registration rates and the two different time frames that have been considered for both measures, in total four Hausman tests are performed. Although, it is argued that the test results of this diagnostic test are inferior compared to those obtained from the augmented regression, due to heteroskedasticity in the residuals, they can nevertheless be considered a valuable addition. Surprisingly, the Hausman test provides results in favour of an RE model for the investigation where EA is measured by means of Twitter and therefore contradicts the results of the augmented regression. Nevertheless, as presented in the results of this chapter, even the more efficient RE model provides insignificant estimates for this determinant.

Table A.1: Hausman Test: Twitter 2010-2017

	(b) Fixed	(B) Random	(b-B) Difference	$\sqrt{\text{diag}(V_b - V_B)}$ SE
EA	-47.50849	-47.92234	0.4138493	3.134044
Charger 100km highway	-0.0002859	0.0007589	-0.0010448	0.0004017
Fast Charger 100km highway	-0.0002146	-0.0004643	0.0002497	0.0012915
Disposable Income	0.0001027	0.0001622	-0.0000595	0.0000926
EV Models	0.0723999	0.0658564	0.0065434	0.0059578
LN(Electricity to Diesel Price)	-1.12353	-1.057205	-0.663252	0.4046904
Car Fleet	1.12E-07	-1.76E-07	1.29E-07	1.24E-07
Subsidies	0.0000972	0.0000915	5.62E-06	0.0000196
			$\bar{\chi}^2 (6)$	1.76
			$\text{Prob} > \bar{\chi}^2$	0.7798

Table A.2: Hausman Test: Twitter 2011-2017

	(b) Fixed	(B) Random	(b-B) Difference	$\sqrt{\text{diag}(V_b - V_B)}$ SE
EA	12.50162	6.017815	6.483802	7.027526
Charger 100km highway	-0.0008031	0.0003749	-0.0011781	0.0004044
Fast Charger 100km highway	0.0017305	0.0007199	0.0010106	0.0012105
Disposable Income	0.0000909	0.0001675	-0.0000766	0.0001019
EV Models	0.069148	0.0606662	0.0084818	0.0063188
LN(Electricity to Diesel Price)	-1.792074	-1.447032	-0.3450424	0.4182591
Car Fleet	8.45E-08	-1.51E-08	9.96E-08	1.26E-07
Subsidies	0.0001117	0.0001031	8.64E-06	0.0000194
			$\bar{\chi}^2 (6)$	2.67
			$\text{Prob} > \bar{\chi}^2$	0.6146

Table A.3: Hausman Test: Google Trends 2010-2017

	(b) Fixed	(B) Random	(b-B) Difference	$\sqrt{\text{diag}(V_b - V_B)}$ SE
EA	-0.0211458	-0.0129093	-0.0082365	0.0041448
Charger 100km highway	-0.0002679	0.0008259	-0.0010938	0.000453
Fast Charger 100km highway	-0.0009516	-0.0012872	0.0003356	0.0014672
Disposable Income	0.0000821	0.0001742	-0.000092	0.0001015
EV Models	0.080861	0.0737816	0.0070794	0.0064098
LN(Electricity to Diesel Price)	-2.533623	-2.009204	-0.5244191	0.3677346
Car Fleet	2.47E-07	-9.95E-08	2.57E-07	1.43E-07
Subsidies	0.0001039	0.0000909	0.000013	0.0000219
			$\bar{\chi}^2 (6)$	30.80
			$\text{Prob} > \bar{\chi}^2$	0.0000

Table A.4: Hausman Test: Google Trends 2011-2017

	(b) Fixed	(B) Random	(b-B) Difference	$\sqrt{\text{diag}(V_b - V_B)}$ SE
EA	0.0101685	0.0091216	0.0010469	0.0047079
Charger 100km highway	-0.0009296	0.0002724	-0.001202	0.000412
Fast Charger 100km highway	0.0022055	0.0011558	0.0010497	0.0012376
Disposable Income	0.0000985	0.0001668	-0.0000683	0.0001016
EV Models	0.0697537	0.0604989	0.0092548	0.0063691
LN(Electricity to Diesel Price)	-1.644282	-1.416825	-0.2274569	0.3405237
Car Fleet	1.70E-08	-2.06E-08	3.77E-08	1.36E-07
Subsidies	0.0001086	0.000101	7.64E-06	0.0000193
			$\bar{\chi}^2 (6)$	19.34
			$\text{Prob} > \bar{\chi}^2$	0.0036

COUNTRY INNOVATIVENESS: DIAGNOSTIC TESTS

The following tables present the results of the Hausman (1978) tests for the three different models of Chapter 7. Although, it is argued that the test results of this diagnostic test are inferior compared to those obtained from the augmented regression due to heteroskedasticity in the residuals, they can nevertheless be considered a valuable addition. Surprisingly, the Hausman test provides results in favour of an RE model for the GTS and without charging infrastructure model specification and therefore contradicts the results of the augmented regression. Hence, in case the Hausman test provided more reliable results than the augmented regression, these statistics provide additional support for the final selection of the more efficient RE estimator.

Table B.1: Hausman Test All Variables

	(b) Fixed	(B) Random	(b-B) Difference	$\sqrt{\text{diag}(V_b - V_B)}$ SE
Innovativeness	0.0631605	0.0750608	-0.0119003	0.022856
Disposable Income	0.0000796	0.0001088	-0.0000292	0.0000752
Subsidies	0.0001106	0.000105	-5.65E-06	0.0000118
Chargers 100km highway	-0.0007292	0.0000875	-0.0008167	0.00016
LN(Electricity to Diesel Price)	-1.028905	-0.8472347	-0.1816705	0.2645505
Trend	830.1671	783.1672	46.99989	80.57586
Dwelling House	-0.0585311	-0.005666	-0.0528651	0.0396192
Income 80 to 20	0.21178	0.0467822	0.1649978	0.1195763
Home Ownership	-0.0619888	0.0209869	-0.0829757	0.0386918
			$\bar{\chi}^2 (6)$	15.14
			$\text{Prob} > \bar{\chi}^2$	0.0192

Table B.2: Hausman Test GTS

	(b) Fixed	(B) Random	(b-B) Difference	$\sqrt{\text{diag}(V_b - V_B)}$ SE
Innovativeness	0.0540815	0.0620767	-0.0079952	0.0246302
Disposable Income	0.0000289	0.0000827	-0.0000538	0.0000735
Subsidies	0.0001008	0.0000988	1.9E-06	0.0000155
Chargers 100km highway	-0.0005398	0.0002058	-0.0007456	0.0001517
LN(Electricity to Diesel Price)	-0.751123	-0.9055322	0.1544092	0.2530843
Trend	908.0218	799.5276	108.4942	74.36593
			$\chi^2 (3)$	2.46
			$\text{Prob} > \chi^2$	0.4825

Table B.3: Hausman Test w/o Chargers

	(b) Fixed	(B) Random	(b-B) Difference	$\sqrt{\text{diag}(V_b - V_B)}$ SE
Innovativeness	0.692221	0.721592	-0.0029371	0.0200372
Disposable Income	0.0000819	0.0001026	-0.0000206	0.0000705
Subsidies	0.0001033	0.0001042	-8.9E-07	0.0000113
LN(Electricity to Diesel Price)	-0.9346815	-0.8635883	-0.0800932	0.2186023
Trend	776.2158	794.7238	-18.50802	74.34002
Dwelling House	-0.0390539	-0.0049429	-0.034111	0.037236
Income 80 to 20	0.1388846	0.0708742	0.0680104	0.100814
Home Ownership	-0.0664247	0.0132823	-0.079707	0.0363529
			$\chi^2 (6)$	9.96
			$\text{Prob} > \chi^2$	0.1263

COUNTRY INNOVATIVENESS: HYBRID REGRESSION MODELS

In the following the results of the hybrid regression models for the GTS and w/o charger specifications are presented. Following the structure from the main part of the analysis, initially analyses where each variable is decomposed into its within and between units effects for both regression specifications are executed. Furthermore, for each specification, regressions are performed where innovativeness is represented by a time variant and time invariant variable. The corresponding results are reported in Table C.1

Performing an augmented regression as a second step, it is determined which variables can be included into the hybrid model with an RE specification. The results are reported in Table C.2 and show that only the trend variable for both specifications and the charging infrastructure determinant for the GTS model has to remain in its decomposed form in the final model.

Finally, the results of the final hybrid regression models are reported in Table C.3 for both the time variant and time-invariant innovativeness variables. Additionally, the results for a hybrid model in which only the innovativeness variable obtained an RE specification is reported.

APPENDIX C. COUNTRY INNOVATIVENESS: HYBRID REGRESSION MODELS

Table C.1: Regression Results: Hybrid Models

Variable	Time variant Innovativeness		Time invariant Innovativeness	
	GTS	w/o Chargers	GTS	w/o Chargers
dInnovativeness	5.5571% (0.03857)	7.1674%* (0.03837)		
mInnovativeness	5.8105%*** (0.01802)	8.6332%*** (0.02457)	5.8099%*** (0.01798)	8.6333%*** (0.02452)
dDisposable Income	0.0029% (0.00012)	0.0082% (0.00011)	0.0009% (0.00013)	0.0056% (0.00012)
mDisposable Income	0.0052%* (0.00003)	0.0120%** (0.00006)	0.0052%* (0.00003)	0.0120%** (0.00006)
dSubsidies	0.0101%*** (0.00002)	0.0103%*** (0.00003)	0.0095%*** (0.00002)	0.0096%*** (0.00003)
mSubsidies	0.0043% (0.00003)	0.0104%* (0.00006)	0.0043% (0.00003)	0.0104%* (0.00006)
dChargers 100km highway	-0.0540%*** (0.00019)		-0.0591%*** (0.00016)	
mChargers 100km highway	0.2045%*** (0.00023)		0.2045%*** (0.00023)	
dLN(Electricity to Diesel Price)	-0.7483% (0.60415)	-0.9392% (0.66826)	-0.6682% (0.58381)	-0.7988% (0.64524)
mLN(Electricity to Diesel Price)	-0.7450%* (0.41999)	-0.8673%* (0.45411)	-0.7454%* (0.41901)	-0.8673%* (0.45315)
dTrend	8.7E+5%*** (96.122)	2.3E+5%*** (119.31)	1.2E+6%*** (107.51)	3.5E+5%*** (117.30)
mTrend	omitted	omitted	omitted	omitted
Additional Controls?		✓		✓
Observations	251	251	251	251
χ^2 -score	1376.77***	1086.52***	1396.88***	1236.09***
Within R^2	0.7988	0.8012	0.7954	0.7956
Between R^2	0.8554	0.7424	0.8554	0.7424
Overall R^2	0.8253	0.7740	0.8234	0.7709

Note: The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. All models are based on an RE specification.

*** p < 0.01

** p < 0.05

* p < 0.1

Table C.2: Wald Test for Equivalence of Within and Between Estimates

Tested variables	χ^2 (1)	Prob > χ^2	RE is appropriate?
<i>GTS: Time variant Innovativeness</i>			
dInnovativeness - mInnovativeness = 0	0.01	0.9426	✓
dDisposable Income - mDisposable Income = 0	0.05	0.8293	✓
dSubsidies - mSubsidies = 0	1.73	0.1889	✓
dChargers 100km highway - mChargers 100km highway = 0	78.68	0.0000	X
dLN(Electricity to Diesel Price) - mLN(Electricity to Diesel Price) = 0	0.00	0.9951	✓
dTrend - mTrend = 0	89.24	0.0000	X
<i>w/o Chargers: Time variant Innovativeness</i>			
dInnovativeness - mInnovativeness = 0	0.14	0.7103	✓
dDisposable Income - mDisposable Income = 0	0.11	0.7430	✓
dSubsidies - mSubsidies = 0	0.00	0.9882	✓
dLN(Electricity to Diesel Price) - mLN(Electricity to Diesel Price) = 0	0.01	0.9114	✓
dTrend - mTrend = 0	42.33	0.0000	X
<i>GTS: Time invariant Innovativeness</i>			
dDisposable Income - mDisposable Income = 0	0.13	0.7191	✓
dSubsidies - mSubsidies = 0	1.54	0.2141	✓
dChargers 100km highway - mChargers 100km highways = 0	84.60	0.0000	X
dLN(Electricity to Diesel Price) - mLN(Electricity to Diesel Price) = 0	0.02	0.8863	✓
dTrend - mTrend = 0	76.49	0.0000	X
<i>w/o Chargers: Time invariant Innovativeness</i>			
dDisposable Income - mDisposable Income = 0	0.28	0.5936	✓
dSubsidies - mSubsidies = 0	0.01	0.9099	✓
dLN(Electricity to Diesel Price) - mLN(Electricity to Diesel Price) = 0	0.01	0.9159	✓
dTrend - mTrend = 0	48.46	0.0000	X

Note: The tests are post diagnostic tests for the Hybrid models depicted in Table C.1.

APPENDIX C. COUNTRY INNOVATIVENESS: HYBRID REGRESSION MODELS

Table C.3: Regression Results: Final Hybrid Model

Variable	Time variant Innovativeness				Time invariant Innovativeness	
	Hybrid Final GTS	Hybrid Final w/o Charger	Hybrid Final Only Inno. RE GTS	Hybrid Final Only Inno. RE w/o Charger	Hybrid Final GTS	Hybrid Final w/o Charger
Innovativeness	5.4579%** (0.02207)	8.4108%** (0.03212)	5.7350%*** (0.02089)	7.8564%*** (0.02712)	5.6687%** (0.02578)	8.2717%*** (0.02866)
dInnovativeness						
mInnovativeness						
Disposable Income	0.0049% (0.00004)	0.0116%** (0.00005)			0.0045% (0.00003)	0.0087% (0.00006)
dDisposable Income			0.0030% (0.00012)	0.0084% (0.00011)		
mDisposable Income			0.0053%* (0.00003)	0.0123%** (0.00003)		
Subsidies	0.0082%*** (0.00002)	0.0103%*** (0.00002)			0.0078%*** (0.00002)	0.0095%*** (0.00002)
dSubsidies			0.0101%*** (0.00002)	0.0104%*** (0.00003)		
mSubsidies			0.0043% (0.00003)	0.0106%* (0.00006)		
Chargers 100km highway						
dChargers 100km highway	-0.0515%*** (0.00020)		-0.0538%*** (0.00018)	(0.00016)	-0.0563%*** (0.00017)	
mChargers 100km highway	0.1896%*** (0.00019)		0.2149%*** (0.00023)		0.1927%*** (0.00020)	
LN(Electricity to Diesel Price)	-0.7161% (0.48492)	-0.9411%* (0.56288)			-0.6687% (0.47282)	-0.7706% (0.53466)
dLN(Electricity to Diesel Price)			-0.7508% (0.59348)	-0.9522% (0.65549)		
mLN(Electricity to Diesel Price)			-0.7448%* (0.41811)	-0.8824%** (0.44059)		
Trend						
dTrend	7.7E+5%*** (57.686)	1.8E+5%*** (117.38)	8.6E+5%*** (101.36)	2.2E+5%*** (120.26)	9.2E+5%*** (58.014)	3.8E+5%*** (66.362)
mTrend	omitted	omitted	omitted	omitted	omitted	omitted
Additional Controls?		✓		✓		✓
Observations	251	251	251	251	251	251
χ^2 -score	1145.55***	854.15***	1233.48***	1041.27***	1207.29***	901.01***
Within R^2	0.7982	0.7995	0.7988	0.8011	0.7948	0.7897
Between R^2	0.8477	0.7389	0.8554	0.7419	0.8490	0.7198
Overall R^2	0.8217	0.7709	0.8253	0.7737	0.8205	0.7561

Note: The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. All models are based on an RE specification.

*** p < 0.01

** p < 0.05

* p < 0.1



COUNTRY INNOVATIVENESS: CRE MODEL WITHOUT WITHIN TRANSFORMED TREND VARIABLE

As pointed out in Chapter 7.4.2.2, theoretically, the results of the within component of the CRE model should be the same as the demeaned within effects of the hybrid and the estimates of the FE model. This is however, not the case when not including the within transformed version of the trend variable. To provide support for this claim, the results of the CRE model in which the trend variable is included in its untransformed state are reported in Table D.1. As it can be seen in the results, when including the trend variable without its within transformed form, the coefficients of the within estimates of the three different model specifications differ. This also has an influence on the factors in the regressions that aim to calculate the difference of the between and within effects. It can be seen that $m\beta_H - d\beta_H \neq m\beta_{CRE}$; where β represents the parameters of the determinants of the regression models and the subscripts H and CRE stand for the hybrid and CRE model, respectively. To illustrate the relationship explained in the equation, the example of the main independent variable *Innovativeness* can be used (time-varying case). Inserting the obtained values for this variable into the equation, it can be seen that the difference of the between and within estimates is 0.0751% (6.5949% - 6.5198%) and not 0.4385% as indicated by the CRE model presented here.

APPENDIX D. COUNTRY INNOVATIVENESS: CRE MODEL WITHOUT WITHIN TRANSFORMED TREND VARIABLE

Table D.1: Regression Results: Correlated Random Effects Model without Within Transformed Trend Variable

Variable	Time variant Innovativeness			Time invariant Innovativeness		
	RE	FE	CRE	RE	FE	CRE
Innovativeness	7.7950%*** (0.02922)	6.5198%* (0.03655)	6.5893%* (0.03706)	8.9723%*** (0.02652)	omitted	7.0785%*** (0.02425)
mInnovativeness			0.4385% (0.03283)			
Disposable Income	0.0109%** (0.00005)	0.0080% (0.00011)	0.0087% (0.00011)	0.0103%* (0.00005)	0.0056% (0.00012)	0.0064% (0.00012)
mDisposable Income			-0.0020% (0.00011)			0.0003% (0.00011)
Subsidies	0.0105%*** (0.00002)	0.0111%*** (0.00003)	0.0111%*** (0.00003)	0.0100%*** (0.00002)	0.0104%*** (0.00003)	0.0105%*** (0.00003)
mSubsidies			-0.0035% (0.00006)			-0.0028% (0.00006)
Chargers 100km highway	0.0088% (0.00021)	-0.0729%*** (0.00015)	-0.0722%*** (0.00016)	0.0045% (0.00018)	-0.0778%*** (0.00018)	-0.0771% (0.00018)
mChargers 100km highway			0.2658%*** (0.00032)			0.2702%*** (0.00034)
LN(Electricity to Diesel Price)	-0.8437%* (0.50038)	-1.0236% (0.66677)	-1.0238% (0.67755)	-0.7670% (0.49287)	-0.9021% (0.64692)	-0.9009% (0.65738)
mLN(Electricity to Diesel Price)			0.4440% (0.60233)			0.3201% (0.60178)
Trend	2.5E+05%*** (70.6889)	4.0E+05%*** (116.867)	3.6E+5%*** (120.166)	3.2E+5%*** (72.7266)	6.0E+5%*** (116.971)	5.4E+5%*** (120.697)
mTrend			omitted			omitted
Observations	251	251	251	251	251	251
F-score/ χ^2	850.49***	92.27***	2453.43***	1318.60***	119.09***	2218.44***
Within R^2	0.7914	0.8078	0.8078	0.7871	0.8032	0.8032
Between R^2	0.7473	0.1339	0.8574	0.7436	0.0025	0.8566
Overall R^2	0.7697	0.3575	0.8310	0.7656	0.2409	0.8282

Note: Country Fixed and Random Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. All CRE models are based on an RE specification.

*** p < 0.01

** p < 0.05

* p < 0.1



COUNTRY INNOVATIVENESS: CORRELATED RANDOM EFFECTS REGRESSION MODELS

In the following the results of the correlated random effects (CRE) models for the GTS and w/o charger specifications are presented. Following the structure from the main part of the analysis, initially analyses where the between effects for each variable are added to the RE model for both regression specifications are executed. Furthermore, for each specification, regressions are performed where innovativeness is represented by a time variant and time-invariant variable. The corresponding results are reported in Table E.1

Performing an augmented regression as a second step, it is determined which variables can be included into the CRE model with an RE specification. The results are reported in Table E.2 and show that only for the trend variable for both specifications and the charging infrastructure determinant for the GTS model the between effects component has to remain in the final model.

Finally, the results of the final CRE regression models are reported in Table E.3 for both the time variant and time-invariant innovativeness variable. Additionally, the results for a CRE model in which only the innovativeness variable obtained an RE specification is reported.

APPENDIX E. COUNTRY INNOVATIVENESS: CORRELATED RANDOM EFFECTS REGRESSION MODELS

Table E.1: Regression Results: Correlated Random Effects Models

Variable	Time variant Innovativeness		Time invariant Innovativeness	
	GTS	w/o Chargers	GTS	w/o Chargers
Innovativeness	5.5571% (0.03857)	7.1674%* (0.03837)		
mInnovativeness	0.2375% (0.03331)	1.3669% (0.03658)	5.8078%*** (0.01798)	8.6324%*** (0.02452)
Disposable Income	0.0029% (0.00012)	0.0082% (0.00011)	0.0009% (0.00013)	0.0056% (0.00012)
mDisposable Income	0.0023% (0.00011)	0.0038% (0.00012)	0.0043% (0.00012)	0.0064%** (0.00012)
Subsidies	0.0101%*** (0.00002)	0.0103%*** (0.00003)	0.0095%*** (0.00002)	0.0096%*** (0.00003)
mSubsidies	-0.0058% (0.00004)	0.0001% (0.00008)	-0.0053% (0.00004)	0.0009% (0.00008)
Chargers 100km highway	-0.0540%*** (0.00019)		-0.0591%*** (0.00016)	
mChargers 100km highway	0.2586%*** (0.00029)		0.2637%*** (0.00029)	
LN(Electricity to Diesel Price)	-0.7483% (0.60415)	-0.9392% (0.66826)	-0.6682% (0.58381)	-0.7988% (0.64524)
mLN(Electricity to Diesel Price)	0.0015% (0.53752)	0.0726% (0.65244)	-0.0790% (0.53018)	-0.0690% (0.65424)
dTrend	8.7E+5%*** (96.122)	2.3E+5%*** (119.31)	1.2E+6%*** (107.51)	3.5E+5%*** (117.30)
mTrend	omitted	omitted	omitted	omitted
Additional Controls		✓		✓
Observations	251	251	251	251
χ^2 -score	1372.76***	1085.88***	1393.91***	1235.44***
Within R^2	0.7988	0.8012	0.7954	0.7956
Between R^2	0.8554	0.7424	0.8554	0.7424
Overall R^2	0.8253	0.7740	0.8234	0.7709

Note: The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. All models are based on an RE specification.

*** p < 0.01

** p < 0.05

* p < 0.1

Table E.2: Wald Test for Equivalence of Within and Between Estimates CRE Models

Tested variables	χ^2 (1)	Prob > $\bar{\chi}^2$	RE is appropriate?
<i>GTS: Time variant Innovativeness</i>			
mInnovativeness = 0	0.01	0.9432	✓
mDisposable Income = 0	0.05	0.8286	✓
mSubsidies = 0	1.74	0.1876	✓
mChargers 100km highway = 0	78.61	0.0000	X
mLN(Electricity to Diesel Price) = 0	0.00	0.9977	✓
mTrend = 0	n.a.	n.a.	n.a.
<i>w/o Chargers: Time variant Innovativeness</i>			
mInnovativeness = 0	0.14	0.7105	✓
mDisposable Income = 0	0.11	0.7432	✓
mSubsidies = 0	0.00	0.9896	✓
mLN(Electricity to Diesel Price) = 0	0.01	0.9114	✓
mTrend = 0	n.a.	n.a.	n.a.
<i>GTS: Time invariant Innovativeness</i>			
mDisposable Income = 0	0.13	0.7187	✓
mSubsidies = 0	1.55	0.2129	✓
mChargers 100km highways = 0	84.54	0.0000	X
mLN(Electricity to Diesel Price) = 0	0.02	0.8814	✓
mTrend = 0	n.a.	n.a.	n.a.
<i>w/o Chargers: Time invariant Innovativeness</i>			
mDisposable Income = 0	0.28	0.5937	✓
mSubsidies = 0	0.01	0.9113	✓
mLN(Electricity to Diesel Price) = 0	0.01	0.9159	✓
mTrend = 0	n.a.	n.a.	n.a.

Note: The tests are post diagnostic tests for the Hybrid models depicted in Table E.1

Table E.3: Regression Results: Final Correlated Random Effects Models

Variable	Time variant Innovativeness				Time invariant Innovativeness	
	Hybrid Final GTS	Hybrid Final w/o Charger	Hybrid Final Only Inno. RE GTS	Hybrid Final Only Inno. RE w/o Charger	Hybrid Final GTS	Hybrid Final w/o Charger
Innovativeness	5.4578%** (0.02546)	8.4108%** (0.03212)	5.7224%*** (0.02169)	7.7744%*** (0.02816)	5.4578%** (0.02546)	8.2717%*** (0.02866)
mInnovativeness						
Disposable Income	0.0049% (0.00004)	0.0116%** (0.00005)	0.0029% (0.00012)	0.0084% (0.00011)	0.0049% (0.00004)	0.0087% (0.00006)
mDisposable Income			0.0023% (0.00011)	0.0040% (0.00012)		
Subsidies	0.0082%*** (0.00002)	0.0103%*** (0.00002)	0.0101%*** (0.00002)	0.0104%*** (0.00003)	0.0082%*** (0.00002)	0.0095%*** (0.00002)
mSubsidies			-0.0058% (0.00004)	0.0003% (0.00008)		
Chargers 100km highway	-0.0515%*** (0.00020)		-0.0538%*** (0.00018)		-0.0515%*** (0.00020)	
mChargers 100km highway	0.2412%*** (0.00029)		0.2584%*** (0.00030)		0.2412%*** (0.00029)	
LN(Electricity to Diesel Price)	-0.7161% (0.48489)	-0.9411%* (0.56288)	-0.7506% (0.59401)	-0.9507% (0.65673)	-0.7161% (0.48489)	-0.7706% (0.53466)
mLN(Electricity to Diesel Price)			0.0047% (0.52231)	0.0673% (0.64213)		
dTrend	7.8E+5%*** (55.694)	1.8E+5%*** (74.616)	8.7E+5%*** (100.96)	2.3E+5%*** (120.06)	7.8E+5%*** (55.694)	3.8E+5%*** (66.362)
mTrend	omitted	omitted	omitted	omitted	omitted	omitted
Additional Controls		✓		✓		✓
Observations	251	251	251	251	251	251
χ^2 -score	1145.53***	854.15***	1217.50***	1035.37***	1207.25***	901.01***
Within R^2	0.798	0.7995	0.7988	0.8012	0.7948	0.7897
Between R^2	0.8477	0.7389	0.8554	0.7418	0.8490	0.7198
Overall R^2	0.8217	0.7709	0.8253	0.7736	0.8205	0.7561

Note: The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. All models are based on an RE specification.

*** p < 0.01

** p < 0.05

* p < 0.1



COUNTRY INNOVATIVENESS: EXCLUSION OF SMALL MARKETS

In the following the regression results are presented for the robustness test in which the small car markets are excluded for the model specifications GTS (Table F.1) and w/o charging infrastructure (Table F.2). Following the same structure as in the main part of the analysis, the models are fitted into an FE, RE and three hybrid models.

APPENDIX F. COUNTRY INNOVATIVENESS: EXCLUSION OF SMALL MARKETS

Table F.1: Regression Results: Exclusion Small Car Markets GTS

Variable	Baseline Regressions		Hybrid Models		
	FE	RE	Hybrid	Hybrid Final	Hybrid Final Only Inno. RE
Innovativeness	3.4684% (0.02391)	4.9881%** (0.02104)		4.5200%*** (0.01706)	4.8371%*** (0.01597)
dInnovativeness			3.4684% (0.02420)		
mInnovativeness			5.5304%*** (0.01823)		
Disposable Income	0.0094% (0.00007)	0.0108%*** (0.00004)		0.0059%** (0.00002)	
dDisposable Income			0.0094% (0.00007)		0.0096% (0.00007)
mDisposable Income			0.0050%* (0.00003)		0.0058%** (0.00002)
Subsidies	0.0084%*** (0.00002)	0.0104%*** (0.00002)		0.0087%*** (0.00002)	
dSubsidies			0.0084%*** (0.00002)		0.0086%*** (0.00002)
mSubsidies			0.0082%** (0.00003)		0.0084%** (0.00003)
Chargers 100km highway	-0.0679%*** (0.00018)	-0.0040% (0.00022)			
dChargers 100km highway			-0.0679%*** (0.00018)	-0.0681%*** (0.00018)	-0.0666%*** (0.00018)
mChargers 100km highway			0.2032%*** (0.00023)	0.2033%*** (0.00015)	0.2016%*** (0.00023)
LN(Electricity to Diesel Price)	0.2013% (0.27440)	-0.2176% (0.34663)		0.0670% (0.28254)	
dLN(Electricity to Diesel Price)			0.2013% (0.27769)		0.1825% (0.28751)
mLN(Electricity to Diesel Price)			-0.1840% (0.41815)		-0.1853% (0.40578)
Trend	8.2E+5%*** (79.620)	3.7E+5%*** (62.147)			
dTrend			8.2E+5%*** (80.577)	1.1E+6%*** (52.889)	7.6E+5%*** (80.881)
mTrend			omitted	omitted	omitted
Additional Controls?					
Observations	219	219	219	219	219
F/ χ^2 -score	125.65***	842.29***	4316.05***	3043.52***	3797.58***
Within R^2	0.8739	0.8645	0.8739	0.8735	0.8737
Between R^2	0.5260	0.7545	0.9075	0.9050	0.9069
Overall R^2	0.7042	0.8066	0.8892	0.8879	0.8889

Note: Country Fixed and Random Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. All hybrid models are based on an RE specification.

*** $p < 0.01$

** $p < 0.05$

* $p < 0.1$

Table F.2: Regression Results: Exclusion Small Car Markets w/o Charger

Variable	Baseline Regressions		Hybrid Models		
	FE	RE	Hybrid	Hybrid Final	Hybrid Final Only Inno. RE
Innovativeness	4.8312%* (0.02294)	4.9736%** (0.02100)		4.6487%** (0.02107)	5.2852%*** (0.01759)
dInnovativeness			4.8312%** (0.02333)		
mInnovativeness			6.2925%*** (0.02349)		
Disposable Income	0.0076% (0.00007)	0.0117%** (0.00005)		0.0107%* (0.00006)	
dDisposable Income			0.0076% (0.00007)		0.0077% (0.00007)
mDisposable Income			0.0125%* (0.00007)		0.0131%** (0.00006)
Subsidies	0.0076%*** (0.00002)	0.0090%*** (0.00002)		0.0087%*** (0.00002)	
dSubsidies			0.0076%*** (0.00002)		0.0076%*** (0.00002)
mSubsidies			0.01295%* (0.00007)		0.0131%* (0.00007)
LN(Electricity to Diesel Price)	0.1891% (0.28656)	0.0332% (0.31180)		0.0452% (0.30823)	
dLN(Electricity to Diesel Price)			0.1891% (0.29145)		0.1796% (0.28987)
mLN(Electricity to Diesel Price)			-0.5375% (0.53015)		-0.5560% (0.53605)
Trend	5.5E+5%*** (83.811)	4.0E+5%*** (67.162)			
dTrend			5.5E+5%*** (85.244)	4.4E+6%*** (63.399)	5.4E+5%*** (86.085)
mTrend			omitted	omitted	omitted
Additional Controls?	✓	✓	✓	✓	✓
Observations	219	219	219	219	219
F/ χ^2 -score	96.86***	960.59***	1356.93***	950.75***	1282.12***
Within R^2	0.8696	0.8664	0.8696	0.8669	0.8695
Between R^2	0.5827	0.7567	0.7927	0.7552	0.7915
Overall R^2	0.6887	0.8138	0.8324	0.8122	0.8320

Note: Country Fixed and Random Effects model with standard errors clustered at country level. The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$. All hybrid models are based on an RE specification.

*** p < 0.01

** p < 0.05

* p < 0.1



EV SUBSIDIES: DESCRIPTIVE STATISTICS

The following table presents the descriptive statistics of the unprocessed subsidies granted to EVs in the investigated time frame. As no changes were applied to the other variables, the descriptive statistics of those determinants are the same as in the main part of the investigation. Hence, they are omitted in the Table G.1.

Table G.1: Descriptive Statistics: EV Market allowing for Negative Subsidies

Variable		Mean	Std. Dev.	Min	Max	Observations
Subsidies	overall	3439.332	3726.337	-2548.96	15123.85	N = 319
	between		3258.249	-471.854	13141.52	n = 29
	within		1898.221	-2456.421	10116.83	T = 11
One-Time Subsidies	overall	3117.151	3529.656	-2541.36	14984.63	N = 319
	between		3065.166	-615.4881	12635.72	n = 29
	within		1832.67	-2729.669	9794.647	T = 11
Rebate	overall	1598.258	2430.984	0	9900	N = 319
	between		1824.686	0	6177.273	n = 29
	within		1638.567	-4248.562	6970.985	T = 11
VAT	overall	207.4271	840.9157	-1975.698	4084.536	N = 319
	between		682.4644	-42.46032	2912.297	n = 29
	within		505.9921	-2020.502	3734.219	T = 11
Point of Sales Tax	overall	1251.732	2722	-2541.36	14984.63	N = 319
	between		2664.581	-739.67	12635.72	n = 29
	within		729.7704	-1979.986	5002.121	T = 11
Income Tax	overall	59.73388	439.2034	0	4052.502	N = 319
	between		255.7836	0	1332.501	n = 29
	within		359.9052	-1272.767	2779.735	T = 11
Recurring Subsidies	overall	322.1808	618.7626	-187.3376	6202.211	N = 319
	between		445.9008	-64.21025	2123.141	n = 29
	within		436.2248	-380.6974	5768.513	T = 11



EV SUBSIDIES: DIAGNOSTIC TESTS

As it has been decided to only report the results of the diagnostic tests of the third regression model for each group to avoid unnecessary repetition, the results of the diagnostic tests for the other models are reported in the following. Thereby, the same structure for the tests is followed as in the main part of this thesis. As differences between the model specifications were already pointed out in the main analysis, in case there were any, no further discussion of the results takes place at this stage.

Table H.1: F-Test: Model 1

	Group 1	Group 2	Group 3
F	F(28, 260) = 18.74	F(28, 259) = 13.96	F(28, 212) = 9.46
Prob >F	0.0000	0.0000	0.0000

Table H.2: F-Test: Model 2

	Group 1	Group 2	Group 3
F	F(28, 260) = 18.97	F(28, 259) = 14.05	F(28, 212) = 9.61
Prob >F	0.0000	0.0000	0.0000

APPENDIX H. EV SUBSIDIES: DIAGNOSTIC TESTS

Table H.3: Breusch and Pagan Lagrange Multiplier Test for Random Effects: Model 1

	Group 1		Group 2		Group 3	
	Var	sd = sqrt(VAR)	Var	sd = sqrt(VAR)	Var	sd = sqrt(VAR)
EVReg	4.269434	2.066261	4.269434	2.066261	2.933794	1.712832
e	0.5422889	0.7364027	0.5329554	0.7300379	0.4167902	0.6455929
u	0.7923643	0.8901485	0.364188	0.6034799	0.3809478	0.6172097
	$\bar{\chi}^2(1)$	480.36	$\bar{\chi}^2(1)$	185.79	$\bar{\chi}^2(1)$	144.70
	<u>Prob > $\bar{\chi}^2$</u>	0.0000	<u>Prob > $\bar{\chi}^2$</u>	0.0000	<u>Prob > $\bar{\chi}^2$</u>	0.0000

Table H.4: Breusch and Pagan Lagrange Multiplier Test for Random Effects: Model 2

	Group 1		Group 2		Group 3	
	Var	sd = sqrt(VAR)	Var	sd = sqrt(VAR)	Var	sd = sqrt(VAR)
EVReg	4.269434	2.066261	4.269434	2.066261	2.933794	1.712832
e	0.537723	0.733296	0.5297568	0.727844	0.4127669	0.6424693
u	0.8280535	0.9099745	0.3825144	0.6184775	0.3986782	0.6314097
	$\bar{\chi}^2(1)$	482.98	$\bar{\chi}^2(1)$	188.55	$\bar{\chi}^2(1)$	149.17
	<u>Prob > $\bar{\chi}^2$</u>	0.0000	<u>Prob > $\bar{\chi}^2$</u>	0.0000	<u>Prob > $\bar{\chi}^2$</u>	0.0000

Table H.5: Hausman Test: Model 1

Group 1	(b) Fixed	(B) Random	(b-B) Difference	sqrt(diag($V_b - V_B$)) SE
Subsidies	0.0000743	0.0001017	-0.0000273	0.0000106
LN(Electricity to Diesel Price)	-0.9890055	-0.6785214	-0.3104841	0.1723778
Trend	1071.356	1046.599	24.75686	7.511662
			$\bar{\chi}^2(3)$	10.87
			<u>Prob > $\bar{\chi}^2$</u>	0.0044
Group 2	(b) Fixed	(B) Random	(b-B) Difference	sqrt(diag($V_b - V_B$)) SE
Subsidies	0.0000757	0.0001181	-0.0000424	0.0000143
LN(Electricity to Diesel Price)	-1.074861	-0.4444065	-0.6304545	0.2402703
Trend	1116.419	1016.163	100.2559	16.09433
Chargers 100km highway	-0.0004875	0.0001517	-0.0006374	0.0000999
			$\bar{\chi}^2(3)$	38.83
			<u>Prob > $\bar{\chi}^2$</u>	0.0000
Group 3	(b) Fixed	(B) Random	(b-B) Difference	sqrt(diag($V_b - V_B$)) SE
Subsidies	0.0000783	0.0001002	-0.0000219	0.0000132
LN(Electricity to Diesel Price)	-0.6496201	-0.361296	-0.2883242	0.2298668
Trend	870.2741	720.2032	150.0709	33.97052
Chargers 100km highway	0.0715247	0.2233881	-0.1518634	0.0344548
			$\bar{\chi}^2(3)$	20.31
			<u>Prob > $\bar{\chi}^2$</u>	0.0001

Table H.6: Hausman Test: Model 2

Group 1	(b) Fixed	(B) Random	(b-B) Difference	sqrt(diag($V_b - V_B$)) SE
One-Time Subsidies	0.0000632	0.0000904	-0.0000271	0.0000104
Recurring Subsidies	0.0002424	0.0000254	-0.0000116	0.0000238
LN(Electricity to Diesel Price)	-1.066765	-0.7505741	-0.3161911	0.1697649
Trend	1071.868	1047.878	23.98984	7.319853
$\chi^2 (3)$				10.77
Prob > χ^2				0.0046
Group 2	(b) Fixed	(B) Random	(b-B) Difference	sqrt(diag($V_b - V_B$)) SE
One-Time Subsidies	0.0000657	0.0001067	-0.000041	0.000014
Recurring Subsidies	0.0002253	0.0002642	-0.0000389	0.0000351
LN(Electricity to Diesel Price)	-1.13891	-0.5113532	-0.6275566	0.2365363
Trend	1114.152	1017.674	96.4777	15.754
Chargers 100km highway	-0.0004564	0.0001523	-0.0006087	0.0000982
$\chi^2 (3)$				37.50
Prob > χ^2				0.0000
Group 3	(b) Fixed	(B) Random	(b-B) Difference	sqrt(diag($V_b - V_B$)) SE
One-Time Subsidies	0.0000656	0.0000888	-0.0000232	0.0000132
Recurring Subsidies	0.0002251	0.0002303	-5.17E-06	0.0000277
LN(Electricity to Diesel Price)	-0.7283719	-0.4220634	-0.3063084	0.2267487
Trend	871.8878	724.6881	147.1997	33.28597
Chargers 100km highway	0.0736635	0.2216003	-0.1479367	0.0336949
$\chi^2 (3)$				20.36
Prob > χ^2				0.0001

Table H.7: Hausman Test: Model 3

Group 1	(b) Fixed	(B) Random	(b-B) Difference	$\sqrt{\text{diag}(V_b - V_B)}$ SE
Rebate	0.0000733	0.0000846	-0.0000114	9.04E-06
VAT	0.000028	0.0001119	-0.0000839	0.0000334
POSTax	0.0000337	0.0001168	-0.0000831	0.0000459
Income Tax	-0.0000731	-8.54E-06	-0.0000646	0.0000272
Recurring Subsidies	0.0002508	0.0002585	-7.74E-06	0.0000288
LN(Electricity to Diesel Price)	-1.072505	-0.7278351	-0.3446697	0.1895562
Trend	1074.805	1048.601	26.2037	7.54442
			$\chi^2 (3)$	12.23
			Prob > χ^2	0.0022
Group 2	(b) Fixed	(B) Random	(b-B) Difference	$\sqrt{\text{diag}(V_b - V_B)}$ SE
Rebate	0.0000676	0.0000898	-0.0000222	0.0000116
VAT	0.000015	0.0001506	-0.0001355	0.0000421
POSTax	0.0000824	0.0001306	-0.0000483	0.0000563
Income Tax	-0.0000441	0.0000143	-0.0000585	0.0000346
Recurring Subsidies	0.0002417	0.0002592	-0.0000175	0.000036
LN(Electricity to Diesel Price)	-1.172477	-0.5670099	-0.6054669	0.2359625
Trend	1120.096	1032.028	88.06803	16.47836
Chargers 100km highway	-0.0004553	0.0000577	-0.000513	0.0001071
			$\chi^2 (3)$	28.64
			Prob > χ^2	0.0000
Group 3	(b) Fixed	(B) Random	(b-B) Difference	$\sqrt{\text{diag}(V_b - V_B)}$ SE
Rebate	0.0000724	0.0000677	4.72E-06	0.0000131
VAT	0.0001274	0.0002265	-0.0000992	0.0000426
POSTax	8.41E-06	0.0000853	-0.0000768	0.0000472
Income Tax	0.0000185	2.46E-07	0.0000183	0.0000401
Recurring Subsidies	0.0002129	0.0002098	3.09E-06	0.000029
LN(Electricity to Diesel Price)	-0.7296186	-0.4454643	-0.2841543	0.2270339
Trend	858.2287	709.9349	148.2938	35.51391
Chargers 100km highway	0.0847024	0.2373378	-0.1526354	0.0376312
			$\chi^2 (3)$	18.18
			Prob > χ^2	0.0004

Table H.8: Mundlak Approach for FE vs. RE: Model 1

	Group 1	Group 2	Group 3
χ^2	$\chi^2 (2) = 16.91$	$\chi^2 (3) = 124.31$	$\chi^2 (4) = 40.78$
Prob > χ^2	0.0000	0.0000	0.0000

Table H.9: Mundlak Approach for FE vs. RE: Model 2

	Group 1	Group 2	Group 3
χ^2	$\chi^2 (3) = 16.81$	$\chi^2 (4) = 112.22$	$\chi^2 (5) = 45.71$
Prob > χ^2	0.0000	0.0000	0.0000

Table H.10: VIF Test: Model 1

Variable	Group 1		Group 2		Group 3	
	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
Subsidies	1.03	0.966357	1.18	0.847630	1.34	0.745922
LN(Electricity to Diesel Price)	1.02	0.981066	1.02	0.980649	1.06	0.942861
Trend	1.03	0.967155	1.12	0.895331	1.23	0.812461
Chargers per 100km highway			1.26	0.792619	1.58	0.633743
Mean VIF	1.03		1.14		1.30	

Table H.11: VIF Test: Model 2

Variable	Group 1		Group 2		Group 3	
	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
One-Time Subsidies	1.08	0.922930	1.22	0.817524	1.37	0.729892
Recurring Subsidies	1.05	0.951578	1.05	0.950572	1.06	0.946601
LN(Electricity to Diesel Price)	1.02	0.978804	1.02	0.978447	1.06	0.9420631
Trend	1.03	0.967147	1.12	0.817524	1.23	0.812455
Chargers per 100km highway			1.26	0.791827	1.58	0.633438
Mean VIF	1.05		1.14		1.26	

Table H.12: Ramsey RESET Test: Model 1

	Group 1	Group 2	Group 3
F-score	F(3, 28) = 9.71	F(3, 28) = 2.40	F(3, 28) = 2.27
Prob >F	0.0001	0.0889	0.1025

Table H.13: Ramsey RESET Test: Model 2

	Group 1	Group 2	Group 3
F-score	F(3, 28) = 9.92	F(3, 28) = 2.73	F(3, 28) = 1.70
Prob >F	0.0001	0.0625	0.1899

Figure H.1: EV Heteroskedasticity: Models 1 and 2

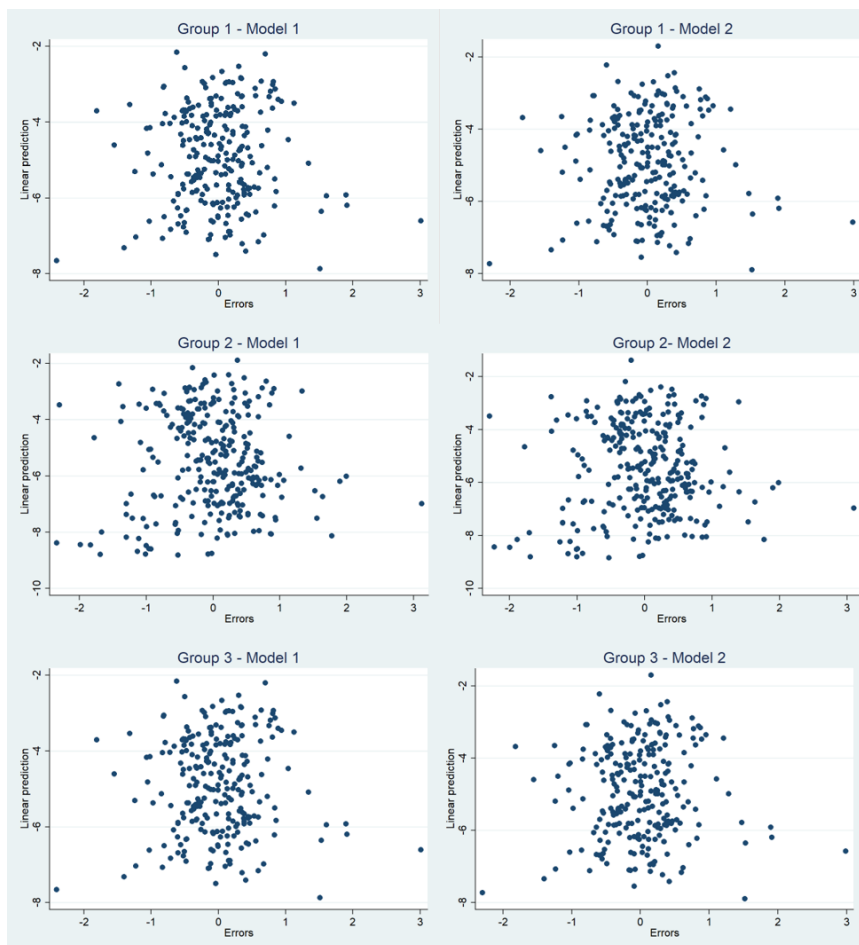


Table H.14: Likelihood Ratio Test: Model 1

	Group 1	Group 2	Group 3
χ^2	$\chi^2(28) = 127.89$	$\chi^2(28) = 99.14$	$\chi^2(28) = 88.17$
Prob > χ^2	0.0000	0.0000	0.0000

Table H.15: Likelihood Ratio Test: Model 2

	Group 1	Group 2	Group 3
χ^2	$\chi^2(28) = 135.52$	$\chi^2(28) = 99.33$	$\chi^2(28) = 88.35$
Prob > χ^2	0.0000	0.0000	0.0000

Table H.16: Wooldridge Test for Autocorrelation: Model 1

	Group 1	Group 2	Group 3
F	$F(1, 28) = 29.977$	$F(1, 28) = 30.074$	$F(1, 28) = 21.404$
Prob > F	0.0000	0.0000	0.0001

Table H.17: Wooldridge Test for Autocorrelation: Model 2

	Group 1	Group 2	Group 3
F	F(1, 28) = 29.271	F(1, 28) = 29.340	F(1, 28) = 21.684
Prob >F	0.0000	0.0000	0.0001

EV SUBSIDIES: DYNAMIC PANEL DATA ALTERNATIVES

In this chapter alternatives in the specification of the GMM dynamic panel data model presented in Chapter 8.1.5.2 are tested. In particular, the differences to the eventual specification reported in the main part of this thesis are as follows: (1) In the first alternative, a one-step instead of a two-step difference GMM is applied. Alternative (2) and (3) report the results of a one-step system GMM and two-step system GMM respectively; Model (4) and (5) in Table I.1 show the results of a two-step difference and two-step system GMM with a lag length of 2.

As it has been determined that an LSDVC approach most likely provides more suitable estimates for the variables, the LSDVC results as well as the best GMM model specification are already reported in the main part of the thesis. Therefore, only the results of deviations in the specification of Model 1 of the first group of regressions are reported in Table I.1. In the same spirit other specifications of this model as well as the models of the other two groups were tested and are available upon request.

APPENDIX I. EV SUBSIDIES: DYNAMIC PANEL DATA ALTERNATIVES

Table I.1: Dynamic Panel Data Model Alternatives EV Market: Model 1

Variable	(1)	(2)	(3)	(4)	(5)
L.ln(EV registration share)	0.5393%*** (0.14632)	0.6593%*** (0.08309)	0.7440%*** (0.15319)	0.4351% (0.26584)	0.5850%*** (0.12899)
L2.ln(EV registration share)				0.1118% (0.12248)	0.2270%*** (0.06431)
Subsidies	0.0057%*** (0.00002)	0.0073%*** (0.00002)	0.0046% (0.00003)	0.0052% (0.00003)	0.0048% (0.00004)
LN(Electricity to Diesel Price)	-0.4135% (0.61815)	0.1649% (0.26678)	0.1644% (0.27042)	-0.0137% (0.75744)	0.1409% (0.29650)
Yearly Time-Dummies	✓	✓	✓	✓	✓
Difference/System	Difference	System	System	Difference	System
One-step GMM	✓	✓			
Two-step GMM			✓	✓	✓
Robust	✓	✓	✓	✓	✓
Windmeiyer correction			✓	✓	✓
Othogonal	✓	✓	✓	✓	✓
Observations	237	266	266	208	237
F-score	323.77	391.92	370.45	209.02	183.01
Number of Groups	29	29	29	29	29
Number of Instruments	20	22	22	19	22
Instruments (lags used)	EV (1)	EV (1)	EV (1)	EV (2)	EV (2)
AR(2) probability	0.813	0.768	0.708	0.097	0.032
Hansen test	0.111	0.057	0.057	0.059	0.123

The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** p < 0.01

** p < 0.05

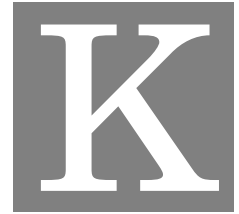
* p < 0.1

BEV SUBSIDIES: DESCRIPTIVE STATISTICS

The following table presents the descriptive statistics of the unprocessed subsidies granted to EVs in the investigated time frame. As no changes were applied to the other variables, the descriptive statistics of those determinants are the same as in the main part of the investigation. Hence, they are omitted in Table J.1.

Table J.1: Descriptive Statistics: BEV Market allowing for Negative Subsidies

Variable		Mean	Std. Dev.	Min	Max	Observations
Subsidies	overall	3842.56	4255.661	-1351.532	19033.51	N = 319
	between		3483.541	0	13010.07	n = 29
	within		2521.349	-3056.368	15249.12	T = 11
One-Time Subsidies	overall	3525.283	4039.86	-1351.532	18663.29	N = 319
	between		3326.64	0	12370.75	n = 29
	within		2366.841	-3352.231	14931.85	T = 11
Rebate	overall	1961.882	3050.316	0	16300	N = 319
	between		2256.879	0	8309.091	n = 29
	within		2090.718	-4915.632	10002.19	T = 11
VAT	overall	315.0239	1237.669	-1802.421	7083.101	N = 319
	between		1146.882	-55.32839	5824.593	n = 29
	within		507.9193	-1600.806	3366.583	T = 11
Point of Sales Tax	overall	1152.42	2553.075	-130.6413	13857.51	N = 319
	between		2495.455	0	11788.88	n = 29
	within		697.6556	-1072.449	6186.45	T = 11
Income Tax	overall	95.95679	673.2979	0	5605.004	N = 319
	between		392.123	0	1983.183	n = 29
	within		551.729	-1887.226	3717.778	T = 11
Recurring Subsidies	overall	317.2773	867.8175	-292.2934	12146.02	N = 319
	between		443.4281	-106.9515	1793.048	n = 29
	within		750.108	-813.7092	11230.61	T = 11



BEV SUBSIDIES: DIAGNOSTIC TESTS

As it has been decided to only report the results of the diagnostic tests of the third regression model for each group to avoid unnecessary repetition, the results of the diagnostic tests for the other models are reported in the following. Thereby, the same structure for the tests is followed as in the main part of this thesis. As differences between the model specifications were already pointed out in the main analysis, in case there were any, no further discussion of the results takes place at this stage.

Table K.1: F-Test: Model 1

	Group 1	Group 2	Group 3
F	$F(28, 262) = 18.22$	$F(28, 261) = 12.59$	$F(28, 216) = 7.84$
Prob >F	0.0000	0.0000	0.0000

Table K.2: F-Test: Model 2

	Group 1	Group 2	Group 3
F	$F(28, 261) = 18.14$	$F(28, 260) = 12.54$	$F(28, 215) = 7.78$
Prob >F	0.0000	0.0000	0.0000

APPENDIX K. BEV SUBSIDIES: DIAGNOSTIC TESTS

Table K.3: Breusch and Pagan Lagrange Multiplier Test for Random Effects: Model 1

	Group 1		Group 2		Group 3	
	Var	sd = sqrt(VAR)	Var	sd = sqrt(VAR)	Var	sd = sqrt(VAR)
BEVReg	3.770864	1.941871	3.770864	1.941871	2.740304	1.655386
e	0.5255421	0.7249428	0.5261917	0.7253907	0.4273418	0.6537138
u	0.7770278	0.8814918	0.3836607	0.6194035	0.3114932	0.5581158
	$\bar{\chi}^2 (1)$	425.86	$\bar{\chi}^2 (1)$	172.97	$\bar{\chi}^2 (1)$	108.80
	<u>Prob > $\bar{\chi}^2$</u>	0.0000	<u>Prob > $\bar{\chi}^2$</u>	0.0000	<u>Prob > $\bar{\chi}^2$</u>	0.0000

Table K.4: Breusch and Pagan Lagrange Multiplier Test for Random Effects: Model 2

	Group 1		Group 2		Group 3	
	Var	sd = sqrt(VAR)	Var	sd = sqrt(VAR)	Var	sd = sqrt(VAR)
BEVReg	3.770864	1.941871	3.770864	1.941871	2.740304	1.655386
e	0.5269096	0.7258854	0.5276391	0.7263877	0.4293036	0.6552126
u	0.8098069	0.8998927	0.3893171	0.6239528	0.3269584	0.5718027
	$\bar{\chi}^2 (1)$	426.47	$\bar{\chi}^2 (1)$	171.43	$\bar{\chi}^2 (1)$	108.08
	<u>Prob > $\bar{\chi}^2$</u>	0.0000	<u>Prob > $\bar{\chi}^2$</u>	0.0000	<u>Prob > $\bar{\chi}^2$</u>	0.0000

Table K.5: Hausman Test: Model 1

Group 1	(b) Fixed	(B) Random	(b-B) Difference	sqrt(diag($V_b - V_B$)) SE
Subsidies	0.0000586	0.0000804	-0.0000218	7.04E-06
LN(Electricity to Diesel Price)	-0.735966	-0.4720916	-0.2638744	0.1693837
Trend	954.934	927.4014	27.53258	7.646221
			$\bar{\chi}^2 (3)$	13.05
			<u>Prob > $\bar{\chi}^2$</u>	0.0015
Group 2	(b) Fixed	(B) Random	(b-B) Difference	sqrt(diag($V_b - V_B$)) SE
Subsidies	0.0000595	0.0000897	-0.0000302	9.21E-06
LN(Electricity to Diesel Price)	-0.7639528	-0.2576716	-0.5062812	0.2301313
Trend	970.1596	877.7641	92.39543	15.83691
Chargers 100km highway	-0.000168	0.0003792	-0.0005472	0.0000949
			$\bar{\chi}^2 (3)$	34.14
			<u>Prob > $\bar{\chi}^2$</u>	0.0000
Group 3	(b) Fixed	(B) Random	(b-B) Difference	sqrt(diag($V_b - V_B$)) SE
Subsidies	0.0000661	0.000085	-0.0000189	9.99E-06
LN(Electricity to Diesel Price)	-0.8270627	-0.4675805	-0.3594822	0.2496278
Trend	775.8839	609.5369	166.3469	37.00779
Chargers 100km highway	0.0974997	0.2608337	-0.163334	0.03737
			$\bar{\chi}^2 (3)$	20.83
			<u>Prob > $\bar{\chi}^2$</u>	0.0001

Table K.6: Hausman Test: Model 2

Group 1	(b) Fixed	(B) Random	(b-B) Difference	sqrt(diag($V_b - V_B$)) SE
One-Time Subsidies	0.0000546	0.0000783	-0.0000237	7.53E-06
Recurring Subsidies	0.0000881	0.0000912	-3.14E-06	8.40E-06
LN(Electricity to Diesel Price)	-0.7602467	-0.4875413	-0.2727054	0.1688027
Trend	956.6892	928.7841	27.90506	7.785126
$\chi^2 (3)$				12.93
Prob > χ^2				0.0016
Group 2	(b) Fixed	(B) Random	(b-B) Difference	sqrt(diag($V_b - V_B$)) SE
One-Time Subsidies	0.0000557	0.0000891	-0.0000334	9.98E-06
Recurring Subsidies	0.0000873	0.0000933	-5.99E-06	0.0000122
LN(Electricity to Diesel Price)	-0.7861344	-0.2632897	-0.5228447	0.2318701
Trend	971.4205	878.5405	92.88004	15.94282
Chargers 100km highway	-0.0001636	0.0003755	-0.0005392	0.0000945
$\chi^2 (3)$				34.05
Prob > χ^2				0.0000
Group 3	(b) Fixed	(B) Random	(b-B) Difference	sqrt(diag($V_b - V_B$)) SE
One-Time Subsidies	0.0000651	0.0000867	-0.0000216	0.000011
Recurring Subsidies	0.0000715	0.0000703	1.14E-06	0.0000119
LN(Electricity to Diesel Price)	-0.8324009	-0.4658498	-0.3665511	0.2488049
Trend	776.475	612.5772	163.8979	36.96514
Chargers 100km highway	0.0975356	0.2565018	-0.1589662	0.0368216
$\chi^2 (3)$				20.31
Prob > χ^2				0.0001

APPENDIX K. BEV SUBSIDIES: DIAGNOSTIC TESTS

Table K.7: Hausman Test: Model 3

Group 1	(b) Fixed	(B) Random	(b-B) Difference	$\sqrt{\text{diag}(V_b - V_B)}$ SE
Rebate	0.0000727	0.0000772	-4.56E-06	7.49E-06
VAT	-0.0000186	0.0001533	-0.0001719	0.0000498
POSTax	-0.0000127	0.0000895	-0.0001022	0.0000429
Income Tax	-0.0000211	0.0000214	-0.0000425	0.0000184
Recurring Subsidies	0.0000958	0.0000866	916E-06	0.0000111
LN(Electricity to Diesel Price)	-0.7550238	-0.4288313	-0.3261925	0.1947933
Trend	959.4787	920.7144	38.7643	9.030457
			$\chi^2 (3)$	18.80
			Prob > χ^2	0.0001
Group 2	(b) Fixed	(B) Random	(b-B) Difference	$\sqrt{\text{diag}(V_b - V_B)}$ SE
Rebate	0.0000726	0.0000814	-8.88E-06	8.98E-06
VAT	-0.0000187	0.0001734	-0.0001921	0.0000549
POSTax	-0.0000112	0.0000783	-0.0000895	0.000055
Income Tax	-0.0000206	0.0000186	-0.0000393	0.0000219
Recurring Subsidies	0.0000958	0.0000852	0.0000106	0.0000128
LN(Electricity to Diesel Price)	-0.7572062	-0.3053355	-0.4518707	0.226208
Trend	960.4593	886.4176	74.04169	16.9086
Chargers 100km highway	-0.0000104	0.000295	-0.0003054	0.0001135
			$\chi^2 (3)$	19.24
			Prob > χ^2	0.0001
Group 3	(b) Fixed	(B) Random	(b-B) Difference	$\sqrt{\text{diag}(V_b - V_B)}$ SE
Rebate	0.0000758	0.0000666	9.23E-06	0.0000121
VAT	0.0000698	0.0002395	-0.0001697	0.0000643
POSTax	5.66E-06	0.0000793	-0.0000736	0.0000482
Income Tax	-6.34E-06	-0.0000135	7.15E-06	0.0000322
Recurring Subsidies	0.0000722	0.0000546	0.0000176	0.0000134
LN(Electricity to Diesel Price)	-0.8446422	-0.4347919	-0.4098504	0.2580945
Trend	777.2302	599.2858	177.9445	42.06358
Chargers 100km highway	0.1021169	0.2748122	-0.1726953	0.043155
			$\chi^2 (3)$	18.97
			Prob > χ^2	0.0003

Table K.8: Mundlak Approach for FE vs. RE: Model 1

	Group 1	Group 2	Group 3
χ^2	$\chi^2 (3) = 13.35$	$\chi^2 (4) = 103.93$	$\chi^2 (4) = 25.76$
Prob > χ^2	0.0000	0.0000	0.0000

Table K.9: Mundlak Approach for FE vs. RE: Model 2

	Group 1	Group 2	Group 3
χ^2	$\chi^2 (3) = 13.75$	$\chi^2 (4) = 133.24$	$\chi^2 (5) = 26.83$
Prob > χ^2	0.0033	0.0000	0.0001

Table K.10: VIF Test: Model 1

Variable	Group 1		Group 2		Group 3	
	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
Subsidies	1.06	0.941321	1.26	0.793644	1.33	0.749182
LN(Electricity to Diesel Price)	1.02	0.980382	1.02	0.980229	1.06	0.943883
Trend	1.06	0.943063	1.12	0.889073	1.22	0.822326
Chargers per 100km highway			1.31	0.762587	1.54	0.650206
Mean VIF	1.05		1.18		1.29	

Table K.11: VIF Test: Model 2

Variable	Group 1		Group 2		Group 3	
	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
One-Time Subsidies	1.07	0.931440	1.26	0.795757	1.35	0.741374
Recurring Subsidies	1.02	0.980805	1.03	0.974809	1.02	0.982548
LN(Electricity to Diesel Price)	1.02	0.979491	1.02	0.979348	1.06	0.942042
Trend	1.06	0.931440	1.12	0.888968	1.22	0.822218
Chargers per 100km highway			1.31	0.762443	1.55	0.646795
Mean VIF	1.04		1.15		1.24	

Table K.12: Ramsey RESET Test: Model 1

	Group 1	Group 2	Group 3
F-score	$F(3, 28) = 7.23$	$F(3, 28) = 7.25$	$F(3, 28) = 1.28$
Prob >F	0.0010	0.0010	0.2991

Table K.13: Ramsey RESET Test: Model 2

	Group 1	Group 2	Group 3
F-score	$F(3, 28) = 6.86$	$F(3, 28) = 7.27$	$F(3, 28) = 1.21$
Prob >F	0.0013	0.0009	0.3249

Figure K.1: BEV Heteroskedasticity: Models 1 and 2

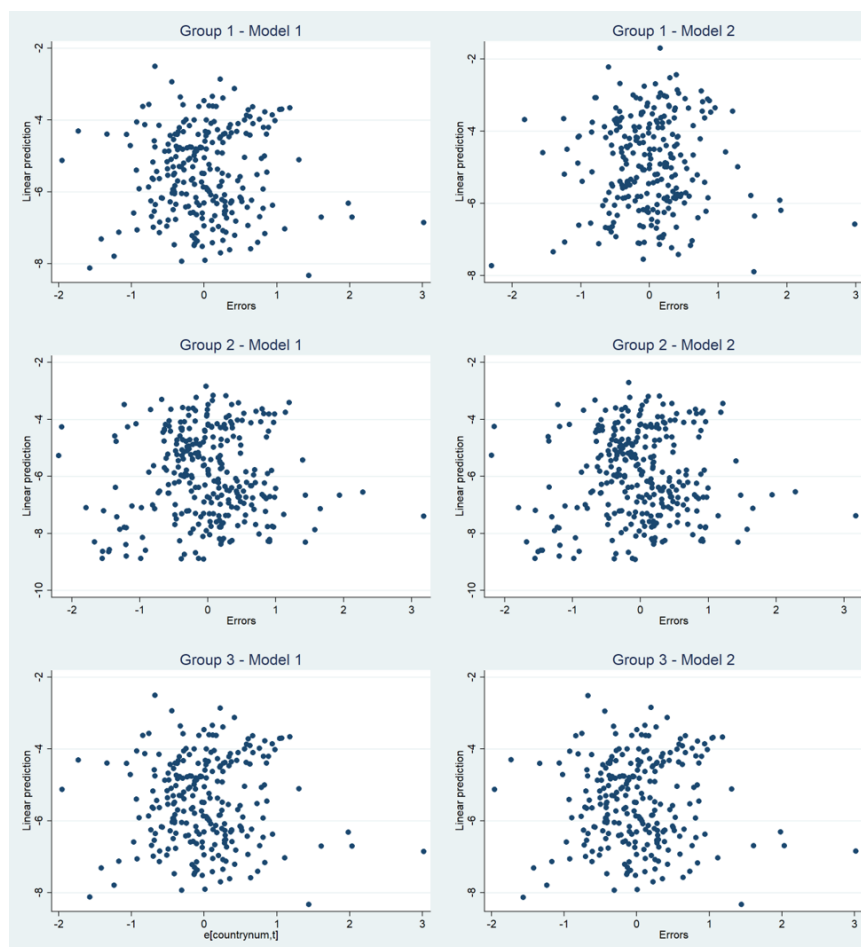


Table K.14: Likelihood Ratio Test: Model 1

	Group 1	Group 2	Group 3
χ^2	$\chi^2(28) = 140.99$	$\chi^2(28) = 106.52$	$\chi^2(28) = 92.40$
Prob > χ^2	0.0000	0.0000	0.0000

Table K.15: Likelihood Ratio Test: Model 2

	Group 1	Group 2	Group 3
χ^2	$\chi^2(28) = 141.26$	$\chi^2(28) = 106.20$	$\chi^2(28) = 92.37$
Prob > χ^2	0.0000	0.0000	0.0000

Table K.16: Wooldridge Test for Autocorrelation: Model 1

	Group 1	Group 2	Group 3
F	F(1, 28) = 11.297	F(1, 28) = 11.916	F(1, 28) = 38.824
Prob > F	0.0018	0.0018	0.0000

Table K.17: Wooldridge Test for Autocorrelation: Model 2

	Group 1	Group 2	Group 3
F	F(1, 28) = 12.013	F(1, 28) = 12.004	F(1, 28) = 37.270
Prob >F	0.0017	0.0017	0.0000



BEV SUBSIDIES: DYNAMIC PANEL DATA ALTERNATIVES

In this chapter alternatives in the specification of the GMM dynamic panel data model presented in Chapter 8.2.5.2 are tested. In particular, the differences to the eventual specification reported in the main part of this thesis are as follows: (1) In the first alternative, a one-step instead of a two-step difference GMM is applied. Alternative (2) and (3) report the results of a one-step system GMM and two-step system GMM respectively; Model (4) and (5) in Table L.1 show the results of a two-step difference and two-step system GMM with a lag length of 2.

As it has been determined that an LSDVC approach most likely provides more suitable estimates for the variables, the LSDVC results as well as the best GMM model specification are already reported in the main part of the thesis. Therefore, only the results of deviations in the specification of Model 1 of the first group of regressions are reported in Table L.1. In the same spirit other specifications of this model as well as the models of the other two groups were tested and are available upon request.

Table L.1: Dynamic Panel Data Model Alternatives BEV Market: Model 1

Variable	(1)	(2)	(3)	(4)	(5)
L.ln(BEV registration share)	0.5246%*** (0.14155)	0.5762%*** (0.09629)	0.7168%*** (0.11183)	0.2681% (0.28988)	0.4247%*** (0.13225)
L2.ln(BEV registration share)				0.0653% (0.12807)	0.2050%** (0.08157)
Subsidies	0.0047%** (0.00002)	0.0077%*** (0.00002)	0.0054%** (0.00003)	0.0057%* (0.00003)	0.0061%** (0.00003)
LN(Electricity to Diesel Price)	-0.4002% (0.65091)	0.1999% (0.30081)	0.2244% (0.31694)	0.4024% (0.78459)	0.3908% (0.31556)
Yearly Time-Dummies	✓	✓	✓	✓	✓
Difference/System	Difference	System	System	Difference	System
One-step GMM	✓	✓			
Two-step GMM			✓	✓	✓
Robust	✓	✓	✓	✓	✓
Windmeiyer correction			✓	✓	✓
Othogonal	✓	✓	✓	✓	✓
Observations	236	265	265	207	236
F-score	258.39	224.88	206.57	207.12	114.54
Number of Groups	29	29	29	29	29
Number of Instruments	20	22	22	19	22
Instruments (lags used)	BEV (1)	BEV (1)	BEV (1)	BEV (2)	BEV (2)
AR(2) probability	0.282	0.242	0.254	0.679	0.253
Hansen test	0.164	0.088	0.088	0.149	0.138

The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** $p < 0.01$

** $p < 0.05$

* $p < 0.1$



PHEV SUBSIDIES: DESCRIPTIVE STATISTICS

The following table presents the descriptive statistics of the unprocessed subsidies granted to EVs in the investigated time frame. As no changes were applied to the other variables, the descriptive statistics of those determinants are the same as in the main part of the investigation. Hence, they are omitted in the Table M.1.

Table M.1: Descriptive Statistics: PHEV Market allowing for Negative Subsidies

Variable		Mean	Std. Dev.	Min	Max	Observations
Subsidies	overall	2959.357	3592.288	-5097.92	16403.59	N = 319
	between		3251.933	-1120.289	13991.39	n = 29
	within		1631.568	-2738.292	7522.976	T = 11
One-Time Subsidies	overall	2640.315	3395.555	-5082.72	16111.75	N = 319
	between		3039.642	-1371.807	13482.55	n = 29
	within		1606.525	-2778.754	7877.422	T = 11
Rebate	overall	1166.453	1966.249	0	7377.262	N = 319
	between		1503.036	0	4816.127	n = 29
	within		1295.399	-3649.674	5166.453	T = 11
VAT	overall	99.83031	730.8334	-2148.974	4656.717	N = 319
	between		474.7762	-29.59225	2540.027	n = 29
	within		561.955	-2440.197	4101.856	T = 11
Point of Sales Tax	overall	1350.521	3012.941	-5082.72	1611.75	N = 319
	between		2872.876	-1495.989	13482.55	n = 29
	within		1041.123	-4068.548	4465.118	T = 11
Income Tax	overall	23.51097	241.677	0	2500	N = 319
	between		126.6105	0	681.8182	n = 29
	within		207.0788	-658.3072	1841.693	T = 11
Recurring Subsidies	overall	319.0421	568.2865	-255.3196	3632.166	N = 319
	between		510.4308	-21.46896	2453.233	n = 29
	within		265.7121	-583.2075	2574.725	T = 11

PHEV SUBSIDIES: DIAGNOSTIC TESTS

As it has been decided to only report the results of the diagnostic tests of the third regression model for each group to avoid unnecessary repetition, the results of the diagnostic tests for the other models are reported in the following. Thereby, the same structure for the tests is followed as in the main part of this thesis. As differences between the model specifications were already pointed out in the main analysis, in case there were any, no further discussion of the results takes place at this stage.

Table N.1: F-Test: Model 1

	Group 1	Group 2	Group 3
F	F(28, 232) = 9.38	F(28, 231) = 7.60	F(28, 210) = 8.16
Prob >F	0.0000	0.0000	0.0000

Table N.2: F-Test: Model 2

	Group 1	Group 2	Group 3
F	F(28, 231) = 10.65	F(28, 230) = 8.28	F(28, 209) = 10.11
Prob >F	0.0000	0.0000	0.0000

APPENDIX N. PHEV SUBSIDIES: DIAGNOSTIC TESTS

Table N.3: Breusch and Pagan Lagrange Multiplier Test for Random Effects: Model 1

	Group 1		Group 2		Group 3	
	Var	sd = sqrt(VAR)	Var	sd = sqrt(VAR)	Var	sd = sqrt(VAR)
PHEVReg	5.031856	2.24318	5.031856	2.24318	4.196034	2.048422
e	1.103391	1.050424	1.101977	1.049751	0.9307721	0.9647653
u	0.7278577	0.8531457	0.5242368	0.724042	0.782777	0.8847468
	$\bar{\chi}^2(1)$	225.63	$\bar{\chi}^2(1)$	113.96	$\bar{\chi}^2(1)$	119.06
	Prob > $\bar{\chi}^2$	0.0000	Prob > $\bar{\chi}^2$	0.0000	Prob > $\bar{\chi}^2$	0.0000

Table N.4: Breusch and Pagan Lagrange Multiplier Test for Random Effects: Model 2

	Group 1		Group 2		Group 3	
	Var	sd = sqrt(VAR)	Var	sd = sqrt(VAR)	Var	sd = sqrt(VAR)
PHEVReg	5.031856	2.24318	5.031856	2.24318	4.196034	2.048422
e	1.010102	1.005039	1.014486	1.007217	0.8051326	0.8972918
u	0.7735742	0.8795307	0.55225	0.7431352	0.8251578	0.908382
	$\bar{\chi}^2(1)$	249.19	$\bar{\chi}^2(1)$	127.58	$\bar{\chi}^2(1)$	145.17
	Prob > $\bar{\chi}^2$	0.0000	Prob > $\bar{\chi}^2$	0.0000	Prob > $\bar{\chi}^2$	0.0000

Table N.5: Hausman Test: Model 1

Group 1	(b) Fixed	(B) Random	(b-B) Difference	sqrt(diag($V_b - V_B$)) SE
Subsidies	0.000146	0.0001568	-0.0000108	0.0000269
LN(Electricity to Diesel Price)	0.2376076	0.4632267	-0.225619	0.388195
Trend	1236.976	1218.014	18.96176	12.1676
			$\bar{\chi}^2(3)$	5.04
			Prob > $\bar{\chi}^2$	0.0806
Group 2	(b) Fixed	(B) Random	(b-B) Difference	sqrt(diag($V_b - V_B$)) SE
Subsidies	0.0001455	0.0001535	-7.94E-06	0.0000294
LN(Electricity to Diesel Price)	0.1734942	0.5471679	-0.3736737	0.4337511
Trend	1274.039	1181.919	92.12027	25.24102
Chargers 100km highway	-0.0003576	0.0003219	-0.0006796	0.0001825
			$\bar{\chi}^2(3)$	15.42
			Prob > $\bar{\chi}^2$	0.0004
Group 3	(b) Fixed	(B) Random	(b-B) Difference	sqrt(diag($V_b - V_B$)) SE
Subsidies	0.0001201	0.0001329	-0.0000128	0.0000238
LN(Electricity to Diesel Price)	0.8279005	0.8370272	-0.0091268	0.3763724
Trend	1231.817	1071.473	160.345	48.66547
Chargers 100km highway	-0.0981154	0.0832042	-0.1813196	0.0542883
			$\bar{\chi}^2(3)$	11.38
			Prob > $\bar{\chi}^2$	0.0098

Table N.6: Hausman Test: Model 2

Group 1	(b) Fixed	(B) Random	(b-B) Difference	sqrt(diag($V_b - V_B$)) SE
One-Time Subsidies	0.0001087	0.0001127	-4.02E-06	0.000024
Recurring Subsidies	0.0012007	0.0009739	0.0002268	0.0001252
LN(Electricity to Diesel Price)	-0.1008286	0.2298654	-0.330694	0.3611012
Trend	1231.998	1218.024	13.97404	11.22513
			$\chi^2 (3)$	1.62
			Prob > χ^2	0.4446
Group 2	(b) Fixed	(B) Random	(b-B) Difference	sqrt(diag($V_b - V_B$)) SE
One-Time Subsidies	0.0001087	0.0001037	5.06E-06	0.0000261
Recurring Subsidies	0.0011982	0.000979	0.0002192	0.0001492
LN(Electricity to Diesel Price)	-0.1024917	0.3444801	-0.4469718	0.4052362
Trend	1233.426	1166.215	67.21083	24.61169
Chargers 100km highway	-0.0000137	0.0004874	-0.000501	0.000179
			$\chi^2 (3)$	7.54
			Prob > χ^2	0.0230
Group 3	(b) Fixed	(B) Random	(b-B) Difference	sqrt(diag($V_b - V_B$)) SE
One-Time Subsidies	0.0000781	0.0000832	-5.17E-06	0.0000203
Recurring Subsidies	0.0013064	0.001102	0.0002045	0.0001086
LN(Electricity to Diesel Price)	0.5315218	0.6487884	-0.1172665	0.3339195
Trend	1194.749	1075.627	119.1217	43.72027
Chargers 100km highway	-0.0600401	0.0759214	-0.1359615	0.0486447
			$\chi^2 (3)$	8.09
			Prob > χ^2	0.0443

Table N.7: Hausman Test: Model 3

Group 1	(b) Fixed	(B) Random	(b-B) Difference	$\sqrt{\text{diag}(V_b - V_B)}$ SE
Rebate	0.0000574	0.0000547	2.67E-06	0.0000238
VAT	0.0000853	0.0001205	-0.0000352	0.0000434
POSTax	0.0001922	0.0001638	0.0000284	0.0000511
Income Tax	-0.0001353	-0.0000173	-0.000118	0.000079
Recurring Subsidies	0.0012234	0.0010054	0.000218	0.0001264
LN(Electricity to Diesel Price)	-0.220541	0.2179608	-0.4385018	0.3622536
Trend	1248.432	1225.422	23.01006	13.4079
			$\chi^2 (3)$	3.11
			Prob > χ^2	0.2115
Group 2	(b) Fixed	(B) Random	(b-B) Difference	$\sqrt{\text{diag}(V_b - V_B)}$ SE
Rebate	0.0000567	0.0000545	2.26E-06	0.0000267
VAT	0.0000828	0.0001417	-0.0000589	0.0000491
POSTax	0.0001951	0.0001418	0.0000533	0.0000546
Income Tax	-0.0001282	-0.0000337	-0.0000945	0.0000896
Recurring Subsidies	0.001211	0.0010053	0.0002057	0.0001473
LN(Electricity to Diesel Price)	-0.2320462	0.3301175	-0.5621636	0.4009117
Trend	1256.614	1178.63	77.98453	25.52219
Chargers 100km highway	-0.0000754	0.0004043	-0.0004797	0.0001725
			$\chi^2 (3)$	9.51
			Prob > χ^2	0.0086
Group 3	(b) Fixed	(B) Random	(b-B) Difference	$\sqrt{\text{diag}(V_b - V_B)}$ SE
Rebate	9.70E-06	4.83E-06	4.87E-06	0.0000216
VAT	0.0000833	0.0001384	-0.0000551	0.0000366
POSTax	0.0001652	0.0001413	0.0000239	0.0000418
Income Tax	-0.0000875	-0.0000783	-9.18E-06	0.0000667
Recurring Subsidies	0.0013153	0.0011331	0.0001822	0.0001052
LN(Electricity to Diesel Price)	0.4220262	0.6294809	-0.2074547	0.3206245
Trend	1191.024	1078.5	112.524	42.97825
Chargers 100km highway	-0.0409928	0.770318	-0.1180246	0.0484689
			$\chi^2 (3)$	7.14
			Prob > χ^2	0.0675

Table N.8: Mundlak Approach for FE vs. RE: Model 1

	Group 1	Group 2	Group 3
χ^2	$\chi^2 (3) = 0.29$	$\chi^2 (4) = 9.71$	$\chi^2 (4) = 12.63$
Prob > χ^2	0.8648	0.0212	0.0132

Table N.9: Mundlak Approach for FE vs. RE: Model 2

	Group 1	Group 2	Group 3
χ^2	$\chi^2 (3) = 3.03$	$\chi^2 (4) = 22.83$	$\chi^2 (5) = 53.52$
Prob > χ^2	0.3869	0.0001	0.0000

Table N.10: VIF Test: Model 1

Variable	Group 1		Group 2		Group 3	
	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
Subsidies	1.01	0.975395	1.09	0.915051	1.28	0.780192
LN(Electricity to Diesel Price)	1.03	0.975395	1.03	0.973108	1.04	0.961062
Trend	1.02	0.976962	1.12	0.842177	1.30	0.766479
Chargers per 100km highway			1.19	0.842177	1.56	0.640766
Mean VIF	1.02		1.11		1.30	

Table N.11: VIF Test: Model 2

Variable	Group 1		Group 2		Group 3	
	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
One-Time Subsidies	1.10	0.910861	1.22	0.819843	1.33	0.750380
Recurring Subsidies	1.09	0.915498	1.10	0.906582	1.09	0.915735
LN(Electricity to Diesel Price)	1.03	0.969046	1.03	0.967736	1.04	0.957596
Trend	1.02	0.976726	1.12	0.894713	1.30	0.766423
Chargers per 100km highway			1.21	0.823758	1.56	0.640738
Mean VIF	1.06		1.14		1.27	

Table N.12: Ramsey RESET Test: Model 1

	Group 1	Group 2	Group 3
F-score	$F(3, 28) = 0.38$	$F(3, 28) = 0.18$	$F(3, 28) = 1.64$
Prob >F	0.7688	0.9080	0.2024

Table N.13: Ramsey RESET Test: Model 2

	Group 1	Group 2	Group 3
F-score	$F(3, 28) = 0.50$	$F(3, 28) = 0.77$	$F(3, 28) = 1.30$
Prob >F	0.6862	0.5198	0.2926

Figure N.1: PHEV Heteroskedasticity: Models 1 and 2

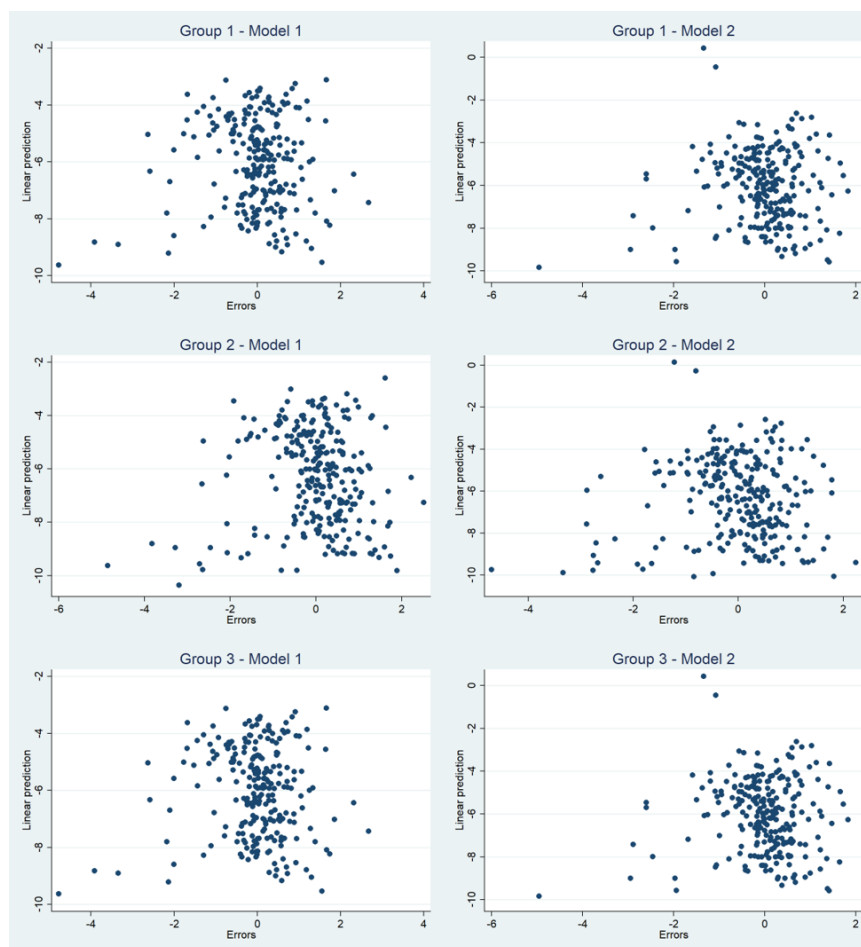


Table N.14: Likelihood Ratio Test: Model 1

	Group 1	Group 2	Group 3
χ^2	$\chi^2(28) = 101.59$	$\chi^2(28) = 97.70$	$\chi^2(28) = 154.05$
Prob > χ^2	0.0000	0.0000	0.0000

Table N.15: Likelihood Ratio Test: Model 2

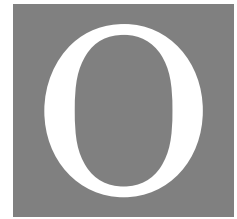
	Group 1	Group 2	Group 3
χ^2	$\chi^2(28) = 109.97$	$\chi^2(28) = 102.94$	$\chi^2(28) = 156.05$
Prob > χ^2	0.0000	0.0000	0.0000

Table N.16: Wooldridge Test for Autocorrelation: Model 1

	Group 1	Group 2	Group 3
F	$F(1, 28) = 14.628$	$F(1, 28) = 14.596$	$F(1, 28) = 11.111$
Prob > F	0.0007	0.0007	0.0024

Table N.17: Wooldridge Test for Autocorrelation: Model 2

	Group 1	Group 2	Group 3
F	F(1, 28) = 20.850	F(1, 28) = 20.711	F(1, 28) = 12.734
Prob >F	0.0001	0.0001	0.0013



PHEV SUBSIDIES: DYNAMIC PANEL DATA ALTERNATIVES

In this chapter alternatives in the specification of the GMM dynamic panel data model presented in Chapter 8.3.5.2 are tested. In particular, the differences to the eventual specification reported in the main part of this thesis are as follows: (1) In the first alternative, a one-step instead of a two-step difference GMM is applied. Alternative (2) and (3) report the results of a one-step system GMM and two-step system GMM respectively; Model (4) and (5) in Table O.1 show the results of a two-step difference and two-step system GMM with a lag length of 2.

As it has been determined that an LSDVC approach most likely provides more suitable estimates for the variables, the LSDVC results as well as the best GMM model specification are reported in the main part of the thesis. Therefore, only the results of deviations in the specification of Model 1 of the first group of regressions are reported in Table O.1. In the same spirit other specifications of this model as well as the models of the other two groups were tested and are available upon request.

APPENDIX O. PHEV SUBSIDIES: DYNAMIC PANEL DATA ALTERNATIVES

Table O.1: Dynamic Panel Data Model Alternatives PHEV Market: Model 1

Variable	(1)	(2)	(3)	(4)	(5)
L.ln(PHEV registration share)	0.6334%*** (0.18404)	0.6631%*** (0.10900)	0.7271%*** (0.12994)	0.5192%** (0.24236)	0.5041%*** (0.17289)
L2.ln(PHEV registration share)	0.0520% (0.06758)	0.1024% (0.07444)	0.0983% (0.07740)	0.1140%* (0.06545)	0.1657%* (0.08206)
L3.ln(PHEV registration share)	0.1077%* (0.06076)	0.1161%* (0.04842)	0.1420%* (0.07412)		
Subsidies	0.0016% (0.00004)	0.0035% (0.00002)	0.0028% (0.00004)	0.0023% (0.00004)	0.0085%* (0.00004)
LN(Electricity to Diesel Price)	-0.0879% (0.45184)	0.1142% (0.23242)	0.0075% (0.35190)	0.2540% (0.66934)	0.2871% (0.49984)
Yearly Time-Dummies	✓	✓	✓	✓	✓
Difference/System	Difference	System	System	Difference	System
One-step GMM	✓	✓			
Two-step GMM			✓	✓	✓
Robust	✓	✓	✓	✓	✓
Windmeiyer correction			✓	✓	✓
Othogonal	✓	✓	✓	✓	✓
Observations	141	170	170	171	200
F-score	67.58	93.99	179.42	96.78	183.54
Number of Groups	28	29	29	29	29
Number of Instruments	17	21	21	18	21
Instruments (lags used)	PHEV (3)	PHEV (3)	PHEV (3)	PHEV (2)	PHEV (2)
AR(2) probability	0.385	0.357	0.376	0.023	0.031
Hansen test	0.163	0.324	0.324	0.271	0.196

The marginal effects are calculated using the following formula: $100 * (e^{\beta} - 1)$

*** $p < 0.01$

** $p < 0.05$

* $p < 0.1$

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