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STRUCTURAL MODELING OF DEMAND AND SUPPLY:
ASSESSING COLLUSION & TAX REFORM IMPACT
ON THE IRISH AUTOMOTIVE MARKET

OLIVIER VAN PARYS

TRINITY COLLEGE
DEPARTMENT OF ECONOMICS
PHD THESIS
2009
DECLARATION

This thesis has not been submitted as an exercise for a degree at any other university. Except where stated, the work described therein was carried out by me alone.

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In this thesis the factors shaping the Irish automotive industry are analyzed using a unique dataset covering purchases of new cars in Ireland during the year 2003.

In chapter 1 of this thesis we set the context of our research. The importance of the industry along with our motivation is laid out.

In chapter 2, I describe the dataset. At its most disaggregate level the data cover 1,277 models. Based on this data set we find a high level of concentration in the industry with three brands capturing a third of the market, especially when we consider that 37 Brands are available to Irish consumers. When performing our analyses at a segment level we encounter some even stronger levels of concentration. We conclude that collusion within this industry is a strong possibility especially if we accept the Structure Conduct Performance paradigm from Bain.

Having established the important stakes in that industry for firms, consumers and the government, we implement in Chapter 3 a discrete choice model using aggregate data and consistent with microeconomic theory. Based on game theory we also model supply under various assumptions regarding firm conduct. Several scenarios are tested to infer to what extent our data validate potential collusion. However no evidence of collusion between car importers or manufacturers is found. I also look at the government’s recent reform to Vehicle Registration Tax motivated an analysis of the potential welfare implications of the change in regime. We simulate the new equilibrium reached using a simultaneous model which factors in the profit maximizing behavior of firms. Doing so allows us to back out firm’s costs that are consistent with the existing equilibrium prior to the tax reform. We find that under our setting, the VRT reform yields gains for both consumers and firms. This is due to a market expansion on the lower end of the market. Assumptions and implementations are discussed in more details within this chapter.

In chapter 4 we deploy more sophisticated modeling techniques allowing us to estimate the parameters of a random coefficient logit model whereby taste heterogeneity across consumers is reflected in the cross substitution patterns. This is an important development since the methodology, first introduced by Berry, Levinsohn and Pakes (BLP) (1995) addresses one of the shortcomings of the logit and nested logit models implemented in the previous chapters. Due to the latest surge of interest coming from Bayesian econometrics we also take this opportunity to compare the results from this estimation strategy to those obtained when we use the General Method of Moments as initially implemented by BLP (1995). We point out possible benefits from using the Bayesian approach which might justify the steep learning curve associated with it.

We conclude by summarizing our key findings and suggest some track for further future research worth pursuing.
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Markups under a Cournot-Nash Equilibrium

Starting from the profit function in 3-1,

The associated FOCs under a Cournot game with fixed marginal costs are

We note that unlike under a Bertrand equilibrium, the Cournot markups do not require any matrix inversion and are therefore likely to be easier to compute providing we can define an inverse demand function expressing price as a function of quantities.

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MARKUPS UNDER A COURNOT-NASH EQUILIBRIUM

STARTING FROM THE PROFIT FUNCTION IN 3-1, THE ASSOCIATED FOCs UNDER A COURNOT GAME WITH FIXED MARGINAL COSTS ARE

WE NOTE THAT UNLIKE UNDER A BERTRAND EQUILIBRIUM, THE COURNOT MARKUPS DO NOT REQUIRE ANY MATRIX INVERSION AND ARE THEREFORE LIKELY TO BE EASIER TO COMPUTE PROVIDING WE CAN DEFINE AN INVERSE DEMAND FUNCTION EXPRESSING PRICE AS A FUNCTION OF QUANTITIES.

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INTRODUCTION TO THE THESIS

1.1 Motivations and Research Objectives

The study of market power and especially the dreaded consequences of monopolistic behaviour have preoccupied researchers as well as policy makers and antitrust-lawyers for decades. A relatively recent popular example is the saga regarding Microsoft. This research project concentrates on the car industry in Ireland, a market that has not been studied previously and presents many interesting features which we discuss in the next section. Our research also adds to the current body of knowledge in several important respects.

Throughout this thesis we illustrate the benefits and insights that can be gained from the latest developments in Demand & Supply Modelling. From an applied perspective we also investigate a question on the lips of many motorists in Ireland: “Are the high prices paid the outcome of collusion within the industry?”. Another question of interest to the government relates to the tax transition regime implemented in 2008 regarding the Vehicle Registration Tax (VRT). Some concerns have been raised regarding the risk associated with this reform. This is not a small matter since the amount raised through the VRT and VAT applied to new car purchases is larger than one billion Euros. In this thesis, the transition regime is also analysed and the effects on government revenue, industry profits and consumer welfare are estimated.

1.2 Data, Methodologies and Contributions

To answer our research questions, substantial efforts were invested in constructing a good quality database. This dataset is available upon request. In chapter 2 we describe this dataset

---

1 Several documents highlight the importance of the case:

2 The author can be contacted at vanparyo@tcd.ie.

3 It is worth mentioning that a paper written in collaboration with Professor Walsh and Dr Mariuzzo (2009) has been based on the current dataset. The findings within this paper were used as part of “Prime time” current affairs TV show broadcasted on RTE1. That working paper was also presented to the Amsterdam EARIE seminar in 2007.
and the efforts involved in liaising with Irish institutions as well as private companies. Following exhaustive cross checking and cleaning we were able to use characteristics, price and volumes on the 1,277 different models that were sold in the country in 2003. In itself this dataset is a noteworthy and useful contribution that allows us to analyse the features of an important market.

To deliver our insights we capitalise on recent advances in demand modelling (Berry (1994) and Berry, Levinsohn & Pakes (1995)). Noteworthy contributions we make through this thesis include comparing Bayesian methodology and the General Method of Moments as originally implemented by BLP (1995) in chapter 4. To date there has been no such direct comparison made between the 2 approaches. We also extend the Bayesian Estimation Technique developed by Jiang, Machanda and Rossi (2007) by including the influence of demographic features on taste heterogeneity of consumers. Their version only deals with random tastes which are unobserved.

1.3 Why the Irish Automotive Industry?

1.3.1 The Introduction of a New Taxation Regime

The market for new cars in Ireland is worth more than 3 billion Euros and represents a sizeable share of what Irish consumers spend. Due to its size it is of interest not only to consumers and firms but also to the Irish government which raises revenue through taxes specific to that market. The recently introduced reform of the Vehicle Registration Tax makes our effort even more timely. In early January, 2009, the government decided to no longer tax cars based on engine size but on CO₂ emissions instead. As part of a gradual implementation however the thresholds brackets applied to engine size were modified in January 2009. In Chapter 2 we implement a method allowing us to gain a better understanding of the potential impact of this tax change on both government revenue and consumer welfare. Here we learn that under the selected tax band transition, both consumers and the industry may have benefited. Indeed we find that consumer welfare is expected to increase by 19% while overall industry profits are expected to increase by 2.4%. This is due to the discriminating nature of the transition tax which imposes a larger burden on larger cars while reducing the toll on lighter vehicles. Our nested model has been able to reflect that consumers, who would not have considered buying a new car, change their mind following the price reduction on some of the lighter models. This change in equilibrium has been triggered by the profit-maximizing behaviours of firms which we also model. What about government revenue? Here we find a

---

4 See Table 3.11.
gloomier picture with an estimated 60 million Euro loss in tax revenue which can be avoided through a softer taxation on the most tax profitable segment, i.e. executive cars. Chapter 3 explains the finer details behind our approach and the related findings.

1.3.2 A Concentrated Industry

Another interesting feature of the car industry has been its consistent profitability. Published reports ranking the most profitable firms in Ireland show that car importers have lodged strong and consistent profits. Such dynamism has generated media scrutiny and consequently triggered interest from the Irish antitrust authorities.

In chapter 2 we analyze the concentration levels. Based on this analysis we find the industry to be quite concentrated with three brands capturing a third of the market sales. These findings provide some potential support for anti-competitive features within the market.

In chapter 3 we test whether our data are consistent with a collusive scenario. We test several scenarios ranging from the most collusive behaviour among the key players in the industry to the most competitive one. Our analysis shows that we do not have enough evidence to support the claim that car importers exhibited collusive behaviour in 2003. Instead we find support for the assertion that current pricing policies reflect a price maximizing behaviour among brands belonging to the same corporation. Assuming this is the case, we conclude that brands owned by the same corporation could be seen as “colluding” but this is not illegal. This does suggest that antitrust authorities should be advised to keep a close eye on future merger proposals within the car industry. These recommendations might only apply in Ireland, however, since the relatively modest profitability of car makers worldwide does little to support our views.

1.4 The need for better substitution patterns

1.4.1 Addressing the IIA issue

Having shown the usefulness of a simultaneous model of demand and supply in chapter 3, chapter 4 addresses some potential shortcomings of using the practical but imperfect nested

---

5 This concentration can be considered high compared to an hypothetical brand share of 2.7% that would materialize when the 37 brands capture equal portions of the market. Under such scenario the top 3 firms would only capture 8% of the market and not 33%.

6 It is worth mentioning that the question of contract exclusivity between manufacturers and importers is not something that can be addressed with our data. Our focus is on horizontal collusion across manufacturers and importers whereby manufacturers and importers are represented by non overlapping set of brands. See 3.2.1 for details.
logit model. Namely we focus on issues related to the problem of Independence of Irrelevant Alternative. While the nested logit model constrains the issue to happen within segments, this is still nonetheless problematic. This is where we implement the methodology first suggested by Berry, Levinsohn and Pakes (1995). Through a random coefficient logit model we allow each consumer to have different tastes for both unobserved and observed characteristics. In doing so, we allow similar consumers to be more likely to substitute toward cars with similar characteristics. This dynamic is not accounted for in the nested logit model whose associated substitution patterns are mostly directed by market shares. Beyond its empirical relevance to the Irish market, a wider contribution of this chapter is that we compare two estimation methods. The original one as suggested by BLP (1995) uses the General Method of Moments. However recent breakthroughs in Markov Chains Monte Carlo sampling technique have led to a surge in papers using a Bayesian Approach. The work from Jiang, Machanda and Rossi (JMR) (2007) is of direct relevance since it implements BLP’s idea within a Bayesian Estimation framework. By comparing the two approaches we find some strong practical value in the Bayesian approach, especially when enriching the dataset with a sample of households which in returns allows us to interact households’ demographic profile with product characteristics. This richer approach implemented in chapter 3 enables us to better understand how consumers might differ in their tastes due to observed characteristics such as gender or age.

Despite the sceptical opinions of “frequentist” regarding the use of priors, the Bayesian Approach converges to estimates in line with economic intuition. On the other hand the GMM method fails to converge when attempting to incorporate the influence of demographic variables. A drawback of the Bayesian Approach is that it is quite computationally intensive. Nonetheless the inconvenience may be worth it if the stakes are high. Tax reforms or an investigation of collusion would fall into that category.

When reporting on both segment and firm level substitutions we find that results from the extended JMR(2009) were the closest to what one expects intuitively. Most exclusive and expensive cars like convertibles, coupes or executive cars are associated to the lowest semi price elasticities which makes sense since these expensive cars are likely to be bought by relatively more wealthy individuals for whom price is less of an issue. Likewise most similar segments, such as Medium and Executive cars or city and compact cars tend to be stronger substitutes for one another, which is also expected since they are the segments with the most similar characteristics. Why is it so important? We show that the estimation methods matter.

---

7 The use of priors involves the analyst to formulate an initial opinion regarding the parameters’ distribution. This can be seen as a lack of objectivity.
and not validating this might be problematic. For instance a merger case could potentially be affected since all the results would be challenged on the basis of the questionable substitution patterns. The same logic can be transposed to recommendations made to government where similar diligence is required. Indeed, let us bear in mind that unreasonable substitution patterns can translate into unreasonable conclusions and misleading recommendations.

1.4.2 Extending the Bayesian Model

Another contribution worth mentioning regarding this chapter is the extension of the Bayesian method of JMR to include the influence of demographic distribution on taste heterogeneity. When doing so the substitutions patterns inferred from the data were the most economically intuitive and in line with previous literature on the automotive industry. While quite computer intensive the results mentioned above were encouraging.
2

DATA SET DESCRIPTION & TOP LINE ANALYSES

2.1 Introduction

In this chapter we describe the data used in the subsequent analyses of the car industry in Ireland. To ensure completeness and accuracy, we have built this dataset from multiple sources through which we cross validate our data. This new dataset provides an interesting case study for investigating oligopoly through some of the latest modelling techniques.

This chapter is organised as follows. Section 2 introduces the data sources and provides information regarding their gathering. Definitions of the variables are provided in section 3. Section 4 provides an overview of the market for new cars in Ireland. Section 5 concludes the chapter.

2.2 The Data Sources

We have collated an extensive database focusing on the number of cars sold in Ireland in 2003. The volume data were provided by the Society of Irish Motorists Industry (SIMI) and are cross validated with data from the Central Statistic Office (CSO) as well as VRT (Vehicle Registration Tax) data provided from the Department of Finance. We completed this database by adding car features and expert ratings from the specialised press and web sites as well as private firms (Car Buyer Guide, carzone.ie). We describe below our main sources in further detail:

2.2.1 The Vehicle Registration Tax Register from the Department of Finance:

By law, each car in Ireland must pay VRT, each vehicle is registered upon purchase, and in many cases the registration happens at the place of purchase with the car dealer registering the car on-line on behalf of the buyer. Because of the implications on government tax revenue, the database maintenance is subjected to a very robust input process with multiple checks to minimize human errors. The availability of these data is instrumental to this thesis. Its quality is validated through matching data from the CSO and the SIMI. The high matching rate between the 3 sources is however expected and when rare divergences occurred the VRT data was given priority since we assumed any discrepancies were likely to be the outcome of data manipulation. It is worth mentioning that these data are not as directly available compared to the SIMI data or the CSO data and extensive discussions were initiated with John Curry and
Tony Murray from the IT unit within the Revenue department. Further to prices and volumes for each model sold in Ireland, we were able to retrieve the following variables:

*Make*

*Model* (Key matching variable used for cross check and merging with other sources such as CBG ratings).

*Version* (Indicative of the level of finish and model range)

*Transmission Type* (Automatic or Manual)

*Engine Type* (Diesel or Petrol)

More details on these variables are available from www.ros.ie which provides the template which needs to be filled by car retailers.

### 2.2.2 The SIMI

This body is the official voice of the motor industry in Ireland. Their membership is based on Vehicle Distributors, Dealers & repairers along with Retailers and many other important operators within the industry in Ireland. SIMI's mission is to represent the views of the industry to the government, state bodies, the media and the motoring public. They compile monthly reports with sales and list prices broken down at a brand level. Therefore we use this data provider to cross validate price and quantities from other sources. The end users of these monthly reports are mostly car dealers (representing the majority of SIMI members) checking their market share so the incentive to provide high quality data in a user friendly format is high. Their main sources is also the Revenue Department and while they may be considered as a duplication of data we already have the fact that their reports are consulted by knowledgable industry suppliers provide us with a further check regarding the validity of volumes and prices for each brand. The data can be downloaded at www.simi.ie in its simplest form. We have received from this body a more detailed version (i.e. at a model level) to enable a model level matching. The reader aiming at replicating our research will want to make special requests like this through www.simi.ie.

### 2.2.3 The Central Statistic Office

The CSO is the main statistical body in Ireland. They provide monthly data ranging from unemployment to inflation indexes. They have a dedicated unit to tourism & transportation statistics, which provided the volume for each brand. While this was a very useful source to fill missing data and build confidence into the data integrity, the key source of price and volumes remain the data supplied by the Revenue office.
2.2.4 Carzone.ie

This web site is a valuable source of information to anyone looking into buying a car (new or second hand). In addition to providing technical details, all new cars are reviewed and rated across specific attributes by industry experts. Those ratings take into account what other experts from the specialised press are thinking about the car under scrutiny. As we will see in the next section, these ratings reflect the benefits sought by potential buyers and therefore usefully complete the picture. This source also offers a good technical spec for each car sold in Ireland. As such it was very useful to incorporate into our dataset variables such as:

- engine size (cc)
- engine power (hp)
- finish
- transmission type
- weight / height / length / width
- mpg

2.2.5 Car Buyer Guide (CBG)

The Car Buyer Guide, the leading car magazine in Ireland publishes information on each car sold in Ireland each month. Their information was extremely useful to validate the information provided by Carzone.ie. Akin to the Carzone data, the CBG source provides the opportunity to complement my dataset with scale based ratings on the following attributes:

- performance
- comfort
- reliability
- Value for money
- Security

The CBG website (www.cbg.ie) is also used to fill any missing variable regarding the technical spec available from carzone.ie. From this data source we were also able to extract information associated to the lifecycle and age of the product through the availability of the year when the product was first introduced to the Irish market and the year when the model was or will be phased out.
2.3 Overview of the Variables & Definitions

2.3.1 Basic Raw Variables

Because product characteristics are essentials when studying demand within a discrete choice framework, great care was taken to ensure both exhaustiveness and accuracy were obtained on car characteristics.

**Volume 2003:**
Volume sold for a given model in units

**Length:**
Length of the car (cm)

**Width:**
Width of the car (cm)

**Height:**
Height of the car (cm)

**Price:**
List price in Euros. Note that for our purpose transaction prices are preferable but in their absence we use list price as proxy.

**Mpg:**
Miles per gallon, which is indicative of the vehicle’s consumption.

**Hp:**
Horsepower, relates to the power of the engine

**Maximum Speed:**
Maximum speed in “Miles per Hour” that can be achieved according to Car Buyer Guide

**Acceleration:**
Time required to go from 0 to 60 mph. Multiple sources were used for cross validation while also minimizing the number of missing variables (CBG, alldatasystems and the Parker Guide).

**Road tax:**
Provided by CBG. Directly related to cubic capacity of engine

*Engine Cubic Capacity:*

Provided by CBG, double checked with alldatasystem and Parker car buyer guide (UK)

*No of doors:*

Take discrete values ranging from 2 to 5 depending on whether the car has 2 doors, 3 doors, 4 or 5 doors.

*Auto:*

A dummy equal to 1 if the car is equipped with automatic gearing system, 0 otherwise, provided by CBG but confirmed in model name, when the letter A appears next to it

*Tiptronic:*

1 if the car is equipped with tiptronic system, 0 otherwise, provided by CBG but confirmed with CSO data, some mode had “tip” written next to it.

*Six Speed:*

1 if the car has 6 speed as opposed to 5, usually found on premium model, provided by CBG, and verified with CSO data (some model have “6s” attached to the name).

*Overall Rating:*

Sourced on carzone.ie this is a rating provided by qualified expert & opinion leaders from specialised press. This composite rating is built by autofinder.ie along with the input from four other media (Car Magazine, 4car, Auto Express and Autotrader).

*Ratings:*

Carzone.ie also rates the following specific attributes on a 0 to 5 scale:

*Handling*

*Comfort*

*Quality*

*Performance*

*Roominess*

*Running Costs*

*Value for Money*
“Newness”:
This is a variable generated using the year of introduction of the new model, again multiple sources were used, with car buyer guides as the primary reference and cross checked and completed by Parker’s guide data. This variable is expressed in number of years.

“Year of planned replacement”:
This variable reflects the announced year of replacement by the manufacturer, this input might have an impact on purchase postponement decisions.

Topgear Rating:
Recorded as an “index” value (1 to 100), this survey is conducted every year by the BBC. The survey for 2003 interviewed owners of 137 cars from 35 manufacturers. Great care is taken by Experian™, a data management specialist company to verify every respondent’s claim to ensure reliability. Car owners who registered their car between 1999 and 2002 qualified as valid respondents. While this variable may give us insight into the “recommendation effect” from current owners, it is important to highlight that owners are mostly from the UK, where tastes may differ from the Irish market.

CBG Rating:
Rating scores from car buyer guide experts, ranking from 1 to 5, where 5 reflects the highest standards achievable.

Make:
Manually punched, and ranging from 1 to 37 (37 make, and 1 “other”).

Range:
Sub model e.g. Alfa(make) 147 (range).

Diesel:
Dummy inferred from vehicle registration tax data, and reflected into document provided by the SIMI containing volume data.

Class:
To reflect classification from the specialised press, the following variable was recorded.
Table 2.1: Number of Cars in each Segment

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>4x4</td>
<td>120</td>
<td>9.40</td>
<td>9.40</td>
</tr>
<tr>
<td>City</td>
<td>227</td>
<td>17.78</td>
<td>27.17</td>
</tr>
<tr>
<td>Compact</td>
<td>278</td>
<td>21.77</td>
<td>48.94</td>
</tr>
<tr>
<td>cv&amp;coupe</td>
<td>49</td>
<td>3.84</td>
<td>52.78</td>
</tr>
<tr>
<td>Exec</td>
<td>222</td>
<td>17.38</td>
<td>70.16</td>
</tr>
<tr>
<td>Medium</td>
<td>249</td>
<td>19.50</td>
<td>89.66</td>
</tr>
<tr>
<td>MPV</td>
<td>132</td>
<td>10.34</td>
<td>100.00</td>
</tr>
<tr>
<td>Total</td>
<td>1,277</td>
<td>100.00</td>
<td></td>
</tr>
</tbody>
</table>

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**Body:**

This variable reflects the overall style of the car:

Table 2.2: Number of Cars grouped by Body Type

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Convertible</td>
<td>42</td>
<td>3.29</td>
<td>3.29</td>
</tr>
<tr>
<td>Estate</td>
<td>122</td>
<td>9.55</td>
<td>12.84</td>
</tr>
<tr>
<td>Hatch-Back</td>
<td>458</td>
<td>35.87</td>
<td>48.71</td>
</tr>
<tr>
<td>MICRO CAR</td>
<td>15</td>
<td>1.17</td>
<td>49.88</td>
</tr>
<tr>
<td>SUV</td>
<td>84</td>
<td>6.58</td>
<td>56.46</td>
</tr>
<tr>
<td>Saloon</td>
<td>351</td>
<td>27.49</td>
<td>83.95</td>
</tr>
<tr>
<td>Sports / Coups</td>
<td>52</td>
<td>4.07</td>
<td>88.02</td>
</tr>
<tr>
<td>Estate</td>
<td>10</td>
<td>0.78</td>
<td>88.80</td>
</tr>
<tr>
<td>medium MPV</td>
<td>57</td>
<td>4.46</td>
<td>93.27</td>
</tr>
<tr>
<td>MPV</td>
<td>52</td>
<td>4.07</td>
<td>97.34</td>
</tr>
<tr>
<td>Saloon</td>
<td>1</td>
<td>0.08</td>
<td>97.42</td>
</tr>
<tr>
<td>SUVs</td>
<td>33</td>
<td>2.58</td>
<td>100.00</td>
</tr>
<tr>
<td>Total</td>
<td>1,277</td>
<td>100.00</td>
<td></td>
</tr>
</tbody>
</table>

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2.3.2 Some Recodes

From the raw variables many of the variables have been recoded for the purpose of including in the analyses. For example, some of the expert ratings from 1 to 5 were transformed into equivalent dummy with 1 for 4 to 5 stars, and zero is the rating given was 3 or below. Some of the physical features have also been recoded. For example, \( \text{hp\_weight} \) is the ratio of horsepower by weight: it reflects the accelerating performance of the car. This ratio has been commonly used in the literature.

We also completed the database by including:

**Dealers:**
Which is a brand specific measure reflecting the strength and presence of the distribution network.

*Number of models:*
Another *brand* specific measure reflecting the breadth and depth of the offering.

*Country:*
It relates to the country of origin (Make legacy), this includes 11 countries used as an alternative to *Make*. It allow for degrees of freedom gains given that the later includes 37 makes.

*Endogeneity Instruments:*
To deal with the endogeneity issue of price, many instruments have also been constructed and grouped into two categories:

*Hausman Taylor type*, which relies on the independence of the demand from one class/segment to another (e.g. mini compact vs. executive).

*BLP type*, another class of instrument based on “competitive pressure” on given characteristics within segment, which are assumed to be reflected into costs, consequently identifying the slope of the demand curve.

### 2.4 The Irish Automobile Market

#### 2.4.1 Market Value & Segmentation

According to the specialised press (CBG, TopGear), the industry is articulated around 8 segments:

- 4 by 4 and *Sport Utility Vehicles* (e.g. Honda CRv, Land Rover)
- *City cars* (Peugeot 206, Ford Fiesta)
- *Compact cars* (Audi A4, Honda Civic, Ford Focus)
- *Multi Purpose Vehicles* or “*Mpv*” (Volswagen Touran, Renault Espace)
- *Executive* (Mercedes C Class, Volvo S40, BMW 500)
- *Medium* (VW Passat, Opel Vectra, Nissan Primera)
- *Convertibles and Coupes* (Toyota MR, Audi TT)

Note that *Convertibles* and *Coupes* are considered as separate segments but due to their weak share, we have grouped them together.
Table 2.3: Segments Volume, Value and corresponding shares

<table>
<thead>
<tr>
<th></th>
<th>Value (€ millions)</th>
<th>Value Share</th>
<th>Volume</th>
<th>Volume Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>compact</td>
<td>854</td>
<td>26.22</td>
<td>41,840</td>
<td>30.9</td>
</tr>
<tr>
<td>City</td>
<td>573</td>
<td>17.57</td>
<td>37,789</td>
<td>27.91</td>
</tr>
<tr>
<td>medium</td>
<td>716</td>
<td>21.96</td>
<td>27,383</td>
<td>20.22</td>
</tr>
<tr>
<td>Exec</td>
<td>580</td>
<td>17.79</td>
<td>12,589</td>
<td>9.3</td>
</tr>
<tr>
<td>MPV</td>
<td>182</td>
<td>5.58</td>
<td>7,555</td>
<td>5.58</td>
</tr>
<tr>
<td>4x4</td>
<td>273</td>
<td>8.38</td>
<td>6,606</td>
<td>4.88</td>
</tr>
<tr>
<td>Cv&amp;coupe</td>
<td>82</td>
<td>2.5</td>
<td>1,652</td>
<td>1.22</td>
</tr>
<tr>
<td>Total</td>
<td>3,260</td>
<td>100</td>
<td>135,414</td>
<td>100</td>
</tr>
</tbody>
</table>

From the above Table, we observe that three segments (Compact, City & Medium) capture nearly 80 percent of the volume and 65 percent of the value shares.

With the exception of MPVs, the smaller segments represent twice as much in value than in volume. One could argue that this outcome simply illustrates economies of scale. We intend to shed further light on that matter within the next chapters through the extraction of price mark ups.

2.4.2 The Brands

37 different makes compete in Ireland, however we have not yet accounted for the fact that different makes belong to the same manufacturer (eg Seat and Audi belongs to Volkswagen, Lexus is owned by Toyota). We will address this point when modelling the supply side of the market in chapter 3.

From Table 4, it is evident that Ford, Toyota and VW are the most popular makes, with sales accounting for more than one third of the market. Under a perfectly competitive environment we would have expected this figure to represent less than 9% of the market (in volume)*.

However since not all makes are competing in the same segment, we look at concentration in the industry at a more disaggregated level.

Table 2.4: Brands distributed in Ireland

<table>
<thead>
<tr>
<th>Make</th>
<th>Total</th>
<th>Make</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>FORD</td>
<td>12.87%</td>
<td>MITSUBISHI</td>
<td>1.17%</td>
</tr>
<tr>
<td>TOYOTA</td>
<td>11.64%</td>
<td>DAEWOO</td>
<td>0.99%</td>
</tr>
<tr>
<td>VOLKSWAGEN</td>
<td>10.49%</td>
<td>LAND ROVER</td>
<td>0.89%</td>
</tr>
</tbody>
</table>

* If all 37 brands were offering the same products we would expect a brand level share of 2.7%.
<table>
<thead>
<tr>
<th>Make</th>
<th>Total</th>
<th>Make</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>NISSAN</td>
<td>9.67%</td>
<td>SAAB</td>
<td>0.70%</td>
</tr>
<tr>
<td>RENAULT</td>
<td>6.99%</td>
<td>ROVER</td>
<td>0.62%</td>
</tr>
<tr>
<td>OPEL</td>
<td>6.06%</td>
<td>KIA</td>
<td>0.53%</td>
</tr>
<tr>
<td>PEUGEOT</td>
<td>5.11%</td>
<td>MINI</td>
<td>0.41%</td>
</tr>
<tr>
<td>HYUNDAI</td>
<td>3.82%</td>
<td>LEXUS</td>
<td>0.31%</td>
</tr>
<tr>
<td>FIAT</td>
<td>3.74%</td>
<td>ALFA ROMEO</td>
<td>0.28%</td>
</tr>
<tr>
<td>MERCEDES-BENZ</td>
<td>3.58%</td>
<td>SUBARU</td>
<td>0.23%</td>
</tr>
<tr>
<td>CITROEN</td>
<td>2.76%</td>
<td>DAIHATSU</td>
<td>0.19%</td>
</tr>
<tr>
<td>MAZDA</td>
<td>2.58%</td>
<td>JAGUAR</td>
<td>0.18%</td>
</tr>
<tr>
<td>BMW</td>
<td>2.55%</td>
<td>CHRYSLER</td>
<td>0.12%</td>
</tr>
<tr>
<td>SEAT</td>
<td>2.48%</td>
<td>ISUZU</td>
<td>0.06%</td>
</tr>
<tr>
<td>SKODA</td>
<td>2.36%</td>
<td>SSANG YONG</td>
<td>0.04%</td>
</tr>
<tr>
<td>AUDI</td>
<td>2.12%</td>
<td>PORSCHE</td>
<td>0.03%</td>
</tr>
<tr>
<td>HONDA</td>
<td>1.96%</td>
<td>SMART</td>
<td>0.02%</td>
</tr>
<tr>
<td>SUZUKI</td>
<td>1.26%</td>
<td>MG</td>
<td>0.00%</td>
</tr>
<tr>
<td>VOLVO</td>
<td>1.21%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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2.4.3 The Levels of Concentration

We investigate the level of concentration in the industry and within each segment through:

C3: The share of the market captured by the 3 largest manufacturers

C5: The share of the market captured by the 5 largest manufacturers.

To put things into perspective, we compare these indicators with what one would expect in a perfectly competitive market with the same number of firms selling non differentiated goods. This benchmark value is flagged by “PC” in Figure 2.1⁹.

⁹ Complications brought it by entry costs are ignored by the “PC” benchmark.
No matter what segments we analyse, the market is clearly concentrated compared to what is expected under perfect competition.

Medium and city segments are the segments where concentration is less acute. If one is to share Bain’s views on the effect of concentration, one expects lower profit margins on these 2 segments. This thesis will shed some further light on the validity of the Bain Paradigm.

Concentration is quite acute for the highly priced segments, namely *Cabriolet & Coupes* as well as for *executive* cars. Could this just be a reflection of entry barriers?

By extracting product mark ups we provide a partial answer to this question by inferring segment level profitability. Higher profitability may be the byproduct of costly market entry where manufacturers need to recover their entry cost. Potential entry barriers are likely to be the dynamic outcome of multiple factors (manufacturing technology, training, plant location with access to more qualified but expensive workers, R&D, advertising accumulated over several years to build a prestigious brand image, etc...).

Appendix 2-1 provides a firm level break down of concentration across each segment. One will notice the near duopoly aspect prevailing within the market for *convertibles* and *coupes*, where Hyundai and Mercedes Benz capture 83% of the sales. This is interesting given the very different positioning between the 2 brands.

### 2.4.4 Exploring the segments further

In Figure 2.2 we have plotted the average price of vehicles sold in each segment versus their respective volume sold. The size of the bubble relates to the relative “attractiveness” of the segment, based on the share of value that could be expected to be captured if each firm present in a given segment were to capture the same value of this segment. Thus the
“attractiveness” of the segment reflects the expected share for each firm present within a segment where none of them has a competitive advantage.

This graph raises some interesting patterns regarding the market:

![Figure 2.2](image)

As one would expect, the higher the expected price in a given segment, the lower the size of the segment. With the exception of the executive car segments, the other niche segments (i.e. low expected turnover segments corresponding to the smaller bubbles) seem to offer a very modest incentive to entry. This seems to be especially true for the Convertible & Coupe segment which is dominated by two players. Hence at a strategic level there could be trade off between market dominance and expected return. It might be relevant to take this fact into account when looking at their respective price cost mark ups to check whether firms are being rewarded for taking risks.

Finally, we are interested in the expected price differences across each segment. Provided the level of non price differentiation is relatively similar between segments, then one would expect the cross price elasticity to be larger in magnitude for segments relatively close on that price dimension (vertical axes). If such expectations are grounded, then based on Table 2.5, we would find the Convertibles & Coupes segment to be rather well protected from the other segments. A good model should be able to reflect such expectations through relatively smaller average cross price elasticities between the convertibles and cars belonging to other segments, whereas average cross price elasticities between city and compact cars should be among the highest. Unfortunately we will illustrate in Chapter 3 that such patterns do not materialize. This motivates us to go beyond the classical nested logit in chapter 4.
As shown in Table 2.6, we have constructed a “comprehensiveness” measure, which is simply the ratio of the number of firms present in a given segment divided by the total number of firms selling cars in the whole Republic of Ireland.

As expected, the “City” segment is among the most covered segment. This is not surprising if we consider that buyers develop a loyalty to the brand through their experience. Indeed many industry analysts believe that “first time new car buyers” tend to be located in this segment, and they also tend to be younger than other new car buyers. It is at this critical stage that car makers acquire new customers, with the hope of keeping them when those same consumers decide to move up the range towards more expensive vehicles. This marketing strategy can also be justified by economic theory through switching costs and lifecycle fluctuations of income. Due to its relatively high price tag, buying a car is a risky experience. A positive experience with a given car will diminish the perceived risk associated with buying another car from that same make compared to buying from a competitor. As one gets older, one also usually gets richer. Thus under the assumption that consumers’ price sensitivity is negatively
correlated to income, firms have an incentive to go for lower markups in the segments most likely to attract first time buyers with of extracting higher markups on the next purchase.

Further details for each segment are provided in Appendix 2.

2.5 Conclusion

This chapter has presented the data that will be used in the empirical part of this thesis. While offering great potential by incorporating many high quality sources, we should also flag its limitations. In particular, since our dataset is a cross section, it limits the breadth of techniques that can be used. For instance, any dynamic techniques involving lagged observations will not be applicable. This is the first time that such a dataset has been compiled which is a significant contribution, however future research efforts would benefit from including most recent years, particularly given the change in the economic climate.

Even within the cross section, however, we have been able to provide a clear outlook for the industry and some level of stability is expected. For instance, we have seen that regardless of the segments the car industry is quite concentrated and this is not likely to change over the short term. Convertible and coupe cars along with executive cars are amongst the most concentrated segments with Mercedes, BMW and Audi representing nearly three quarters of the sales in the executive segment while Hyundai and Mercedes nearly split the convertible and coupe segment into a duopoly. Given this context, the Bain paradigm predicts higher margins in these two segments. To what extent are such expectations valid? This is one of the questions we try to addressed in chapter 3. Likewise we were also able to set some expectations regarding cross substitution patterns by plotting price and quantity across each segment. Based on price proximities, should we expect higher substitution effects between MPV and medium cars than between MPV and 4x4? We invite the reader to keep this question in mind when looking at our demand models in chapter 2 and chapter 3.
Highlighted below are the top sellers in each segment:

Figure 2.3
APPENDIX 2-2

2.5.1.1 Summary of characteristics across segments

To satisfy the reader’s curiosity, we provide some basic tabulations illustrating average features offered in each segment. We have grouped characteristics into 2 categories:

- Physical characteristics
- Ratings from the specialised Press

Characteristics

Table 2.7: Average Characteristics Across Segments (1)

<table>
<thead>
<tr>
<th></th>
<th>Price</th>
<th>0-60 Speed</th>
<th>HP</th>
<th>MPG</th>
<th>enginecc</th>
<th>Weight</th>
<th>Height</th>
<th>Width</th>
</tr>
</thead>
<tbody>
<tr>
<td>4x4</td>
<td>€49,879</td>
<td>12.6</td>
<td>109</td>
<td>153</td>
<td>29.3</td>
<td>2508</td>
<td>1957</td>
<td>176</td>
</tr>
<tr>
<td>City</td>
<td>€16,452</td>
<td>13.9</td>
<td>102</td>
<td>74</td>
<td>47.3</td>
<td>1273</td>
<td>1134</td>
<td>146</td>
</tr>
<tr>
<td>Compact</td>
<td>€23,011</td>
<td>11.8</td>
<td>114</td>
<td>101</td>
<td>44.1</td>
<td>1617</td>
<td>1330</td>
<td>145</td>
</tr>
<tr>
<td>MPV</td>
<td>€32,161</td>
<td>13.0</td>
<td>109</td>
<td>113</td>
<td>38.7</td>
<td>1834</td>
<td>1589</td>
<td>167</td>
</tr>
<tr>
<td>Exec</td>
<td>€54,806</td>
<td>9.4</td>
<td>135</td>
<td>174</td>
<td>34.9</td>
<td>2365</td>
<td>1703</td>
<td>145</td>
</tr>
<tr>
<td>Medium</td>
<td>€29,996</td>
<td>11.1</td>
<td>123</td>
<td>124</td>
<td>40.0</td>
<td>1896</td>
<td>1542</td>
<td>146</td>
</tr>
<tr>
<td>Cv&amp;coupe</td>
<td>€75,517</td>
<td>7.7</td>
<td>144</td>
<td>223</td>
<td>29.6</td>
<td>2758</td>
<td>1558</td>
<td>134</td>
</tr>
<tr>
<td>Total</td>
<td>€34,355</td>
<td>11.7</td>
<td>118</td>
<td>124</td>
<td>39.8</td>
<td>1890</td>
<td>1496</td>
<td>150</td>
</tr>
</tbody>
</table>


Specialised Press ratings

Table 2.8: Average Characteristics Across Segments (2)

<table>
<thead>
<tr>
<th></th>
<th>Length</th>
<th>Newness</th>
<th>Y before replacement</th>
<th>Topgear rating</th>
<th>CBG rating</th>
<th>Stereo</th>
</tr>
</thead>
<tbody>
<tr>
<td>4x4</td>
<td>458</td>
<td>2.7</td>
<td>3.6</td>
<td>82.37</td>
<td>3.72</td>
<td>3.29</td>
</tr>
<tr>
<td>City</td>
<td>380</td>
<td>2.0</td>
<td>4.4</td>
<td>83.80</td>
<td>3.98</td>
<td>3.40</td>
</tr>
<tr>
<td>compact</td>
<td>425</td>
<td>3.1</td>
<td>3.0</td>
<td>83.27</td>
<td>4.04</td>
<td>2.99</td>
</tr>
<tr>
<td>MPV</td>
<td>442</td>
<td>2.2</td>
<td>4.0</td>
<td>82.62</td>
<td>3.95</td>
<td>3.26</td>
</tr>
<tr>
<td>Exec</td>
<td>472</td>
<td>3.1</td>
<td>3.9</td>
<td>85.96</td>
<td>4.07</td>
<td>4.01</td>
</tr>
<tr>
<td>medium</td>
<td>462</td>
<td>2.3</td>
<td>4.2</td>
<td>83.47</td>
<td>4.07</td>
<td>3.68</td>
</tr>
<tr>
<td>Cv&amp;coupe</td>
<td>439</td>
<td>2.9</td>
<td>4.4</td>
<td>84.57</td>
<td>4.24</td>
<td>4.23</td>
</tr>
<tr>
<td>Total</td>
<td>438</td>
<td>2.6</td>
<td>3.8</td>
<td>83.90</td>
<td>4.01</td>
<td>3.48</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Value for money</th>
<th>Running Cost</th>
<th>Room Performance</th>
<th>Quality</th>
<th>Comfort</th>
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3

LOOKING FOR EVIDENCE OF COLLUSION &
INVESTIGATING THE EFFECTS OF THE TAX
REFORM

3.1 Introduction

Over the years, large and consistent profits registered by leading car importers have raised public interest. Should we suspect foul-play? In this chapter we look for evidence of collusion within the industry. In line with the NEIO\textsuperscript{11} literature, we articulate our analyses around a structural model of demand and supply estimated simultaneously. Due to its ability to reduce the IIA property effects we implement the nested logit as the functional form to model demand. The nested logit is also convenient for its trackability and analytical solution when aggregating over consumers. Both demand and supply side are estimated simultaneously to benefit from efficiency gain.

Based on the above specification we are not able to highlight the presence of collusion. Instead, there seems to be evidence of profit maximization at a corporate level. In other words while manufacturers are maximizing profits across their own brands, they do not seem to engage in price agreements which would allow them to charge a premium above expected equilibrium prices under a more competitive market.

In addition we study the potential economic outcome concerning recent announcements from the Irish finance minister on the VRT reform\textsuperscript{12}. Such reform will gradually shift the focus of the tax, currently based on the engine capacity, to carbon tax emissions. While the Tax has still been concerned with engine size over the past 6 months, new rates have been implemented. What impact can we expect from such “transition” on both the industry and government revenues? We explore this question in the second part of the paper. Our findings indicate that the simulated tax transition seem to benefits both consumers and the industry. Under the selected tax band transition, consumer welfare is expected to increase by 19 per cent. The impact on industry profit is interesting. While margins are expected to fall slightly as the industry absorbs some of the tax effect, overall profits are expected to increase by 2.4

\textsuperscript{11} New Empirical Industrial Organisation.

\textsuperscript{12} Source: Department of Revenue – Budget 2007/2008.
per cent. This is due to market expansion driven by more competitive prices in small engine cars.

The chapter is organised as follow:

In section 3.2, we introduce the theory behind the methodology, while in section 3.3 we discuss the methodology. The data are presented in section 3.4 with an overview of the car market in Ireland. The results are reported in section 3.5. Section 3.6 concludes and discusses the policy implications.

3.2 Theoretical Approach

In this section we first discuss the theory and assumptions made in order to explain price settings in the industry. We then explain how we infer marginal cost, without directly observing them, by leveraging the Bertrand-Nash equilibrium assumptions. We subsequently present the options available for investigating the presence of collusion. Finally, we define the theoretical assumptions behind the demand estimation.

3.2.1 Modelling Firms’ Behaviour

To infer firms’ conduct from aggregate sales data we assume that observed market equilibrium prices are set by short-term profit maximizing firms basing their decisions on their knowledge of consumers’ price sensitivity.\(^{13}\)

Defining the profit of a firm \(f\) selling \(n\) products as:

\[
\Pi_f = \left( \frac{P_1}{1+t}Q_1 - Q_1C_1 \right) + \left( \frac{P_2}{1+t}Q_2 - Q_2C_2 \right) + \ldots + \left( \frac{P_n}{1+t}Q_n - Q_nC_n \right) - FC_f
\]

where \(P_n, Q_n, C_n\) stand for the consumer price, quantity and unit cost of product \(n\) respectively, while \(FC_f\) represents firm’s \(f\) fixed cost and \(t\) represent the prevailing tax rate on the market, consequently making \(\frac{P_n}{1+t}\) the net price of good \(n\).\(^{14,15}\)

---

\(^{13}\) Such assumption is a required condition for a Bertrand-Nash Equilibrium to exist. It is not however a sufficient condition.

\(^{14}\) We are also assuming that the same tax rate applies to all 3 goods.

\(^{15}\) Note that the number of product produced enters implicitly the profit function (3-1) through the magnitude of the index \(n\) however this profit function does not allow us to estimate the profit impact of adding an extra product to firm’s \(f\) product line. Our immediate focus is on price change, a variable that both firms and government can impact over the short term. While modifying the firm’s objective function to assess the impact of changing the number of product made available is of great interest, launching a new product can not usually be done over the short term since it requires
Since this firm seeks to set prices that will maximize its profits, it will aim at solving simultaneously the following system of first order conditions:

\[
\begin{align*}
\frac{\partial Q_k}{\partial P_k} \left( \frac{P_k}{1+t} - C_k \right) + \cdots + \frac{\partial Q_k}{\partial P_k} \left( \frac{P_k}{1+t} - C_k \right) + \cdots + \frac{\partial Q_n}{\partial P_n} \left( \frac{P_n}{1+t} - C_n \right) &= - \frac{Q_k}{1+t} \\
\frac{\partial Q_k}{\partial P_k} \left( \frac{P_k}{1+t} - C_k \right) + \cdots + \frac{\partial Q_k}{\partial P_k} \left( \frac{P_k}{1+t} - C_k \right) + \cdots + \frac{\partial Q_n}{\partial P_n} \left( \frac{P_n}{1+t} - C_n \right) &= - \frac{Q_k}{1+t} \\
\frac{\partial Q_k}{\partial P_k} \left( \frac{P_k}{1+t} - C_k \right) + \cdots + \frac{\partial Q_k}{\partial P_k} \left( \frac{P_k}{1+t} - C_k \right) + \cdots + \frac{\partial Q_n}{\partial P_n} \left( \frac{P_n}{1+t} - C_n \right) &= - \frac{Q_n}{1+t}
\end{align*}
\]

For ease of illustration, we replace the markups \( \left( \frac{P_1}{1+t} - C_1 \right), \ldots, \left( \frac{P_k}{1+t} - C_k \right), \ldots, \left( \frac{P_n}{1+t} - C_n \right) \) by \( x_1, \ldots, x_k \) and \( x_n \) respectively and rewrite the FOCs in matrix form as:

\[
\begin{bmatrix}
\frac{\partial Q_1}{\partial P_1} & \cdots & \frac{\partial Q_k}{\partial P_k} & \cdots & \frac{\partial Q_n}{\partial P_n} \\
\frac{\partial Q_1}{\partial P_1} & \cdots & \frac{\partial Q_k}{\partial P_k} & \cdots & \frac{\partial Q_n}{\partial P_n} \\
\frac{\partial Q_1}{\partial P_1} & \cdots & \frac{\partial Q_k}{\partial P_k} & \cdots & \frac{\partial Q_n}{\partial P_n} \\
\frac{\partial Q_1}{\partial P_1} & \cdots & \frac{\partial Q_k}{\partial P_k} & \cdots & \frac{\partial Q_n}{\partial P_n}
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2 \\
x_3 \\
x_n
\end{bmatrix}
= \begin{bmatrix}
\frac{Q_1}{1+t} \\
\frac{Q_2}{1+t} \\
\frac{Q_3}{1+t} \\
\frac{Q_n}{1+t}
\end{bmatrix}
\]

Hence to find the optimum markups, a firm selling \( n \) products needs to solve the following system:\(^{16}\)

---

\(^{16}\) We treat in appendix 3.1 how the first order condition changed when we consider a Cournot equilibrium. Using the results from Feenstra and Levinsohn (1995), we can expect markups to be higher (i.e. costs to be lower) under a Cournot compared to a Bertrand regime, yet equilibrium prices and quantities will be the same under both regimes. This is because we assume that observed prices and quantities are in a Nash-Cournot equilibrium.
For example, assume that the market is supplied by 2 firms producing 3 goods, \( j, k \) and \( l \). Firm \( f1 \) produces \( j \) and \( k \), while firm \( f2 \) only produces product \( l \). There are two possible market structures.

**Scenario 1**: the 2 firms are competitive so the observed market prices are the outcome of the optimisation described above, i.e. each firm solves the following FOC. This will yield a market price consistent with a Bertrand-Nash Equilibrium.\(^\text{17}\) Note that the assumption regarding the competitive behaviours between firms plays a central role since it dictates the functional form below.

\[
\begin{bmatrix}
x_1 \\
x_2 \\
x_3 \\
\end{bmatrix} = \begin{bmatrix}
\frac{\partial Q_j}{\partial P_1} & \frac{\partial Q_j}{\partial P_2} & \ldots & \frac{\partial Q_j}{\partial P_n} \\
\frac{\partial Q_k}{\partial P_1} & \frac{\partial Q_k}{\partial P_2} & \ldots & \frac{\partial Q_k}{\partial P_n} \\
\frac{\partial Q_l}{\partial P_1} & \frac{\partial Q_l}{\partial P_2} & \ldots & \frac{\partial Q_l}{\partial P_n}
\end{bmatrix}^{-1}
\begin{bmatrix}
Q_j \\
Q_k \\
Q_l \\
\end{bmatrix}
\]

**Scenario 2**: the 2 firms collude and the observed market prices are the outcome of each firm solving the following FOC\(^\text{18}\):

\[
\begin{bmatrix}
x_1 \\
x_2 \\
x_3 \\
\end{bmatrix} = \begin{bmatrix}
\frac{\partial Q_j}{\partial P_1} & \frac{\partial Q_j}{\partial P_2} & \ldots & \frac{\partial Q_j}{\partial P_n} \\
\frac{\partial Q_k}{\partial P_1} & \frac{\partial Q_k}{\partial P_2} & \ldots & \frac{\partial Q_k}{\partial P_n} \\
0 & 0 & \ldots & \frac{\partial Q_l}{\partial P_n}
\end{bmatrix}^{-1}
\begin{bmatrix}
Q_j \\
Q_k \\
Q_l \\
\end{bmatrix}
\]

\(^\text{17}\) i.e. None of the competing firms have an incentive to move their price since it would make them worse off.

\(^\text{18}\) Since in this case we will have the 2 firms maximizing \((p_jq_j+p_kq_k+p_lq_l)/(1+t)-(c_jq_j+c_kq_k+c_lq_l)\). In scenario 1 we have firm 1 maximizing \((p_jq_j+p_kq_k)/(1+t)-(c_jq_j+c_kq_k)\) while firm 2 maximizes \((p_lq_l)/(1+t)-(c_lq_l)\).
In the collusion setting above, the 2 firms are in effect behaving as a monopolistic consortium trying to optimize total market profits.

When solving the relevant game, firms will know their marginal costs \( C_j, C_k \) and \( C_l \) but the researcher does not. However we observe market prices and therefore assuming scenario 1, we can infer the respective costs through backward inductions based on the Bertrand-Nash equilibrium assumption as in Mariuzzo, Walsh and Van Parys (2009). This approach is one of the workhorses in NEIO and has been implemented extensively. From backing out and modelling marginal cost in each competing game we are able to identify the conduct which is most supported by our data. We can validate our findings by applying statistical non-nested test as in Jaumandreu and Lorences (2002) or Gasmi, Laffont and Vuong (1992).

While the Bertrand-Nash assumption is instrumental in our ability to back out the marginal costs\(^{19}\), some key points are worth discussing. Firstly, to reach the equilibrium, firms have to be fully aware of their own price elasticities and cross elasticities. Since, by definition, each firm knows that at the prices set, none of the players have an incentive to change their price, each firm must also know the competitors’ cross price elasticity to be able to reach such an outcome. As such this assumption is quite restrictive but necessary for the purpose of the analysis. After consultation with brand managers from various industries, anecdotally we conclude that while most would be incapable of estimating the accurate price elasticities of their own products (let alone the cross price elasticities of their competitors), through experience they are nonetheless able to flag specific price thresholds that could trigger strong competitive reactions. Should the Bertrand-Nash assumption be very remote from the actual price-setting dynamics of the industry, then the expected efficiency gains from the simultaneous estimation of demand and supply would become irrelevant since we end up introducing additional noise. In such situation, one could question the wisdom of using the Nash Equilibrium assumption. However the associated assumptions do not need to be exactly accurate to be of empirical relevance as long as they hold true “by and large”. Since the latter still needs to be true for firms to stay in business and avoid hostile takeovers, the net benefit of using Bertrand-Nash outweighs its cost.\(^{20}\)

\[\text{and associated markups.}\]

\[\text{Implementing more realistic price dynamics such as the one we just described might be possible through the estimation of price reaction functions, however such option is not available in our setting since we use a cross section. We must therefore constrain our investigation to a static game.}\]
3.2.2 Modelling Marginal Costs

Following Berry Levisohn & Pakes (1995), we define the marginal cost of producing a car \( j \) as:

\[
mc_j = e^{w_j' \gamma + u_j} \tag{3-7}
\]

\[
\ln(mc_j) = w_j' \gamma + u_j \tag{3-8}
\]

where \( w_j \) is a vector of the observable characteristics space, \( u_j \) is an index of unobserved cost characteristics and \( \gamma \) is a vector of unknown parameters to be estimated.

It is assumed that the marginal cost is independent of the quantity produced. The assumption of constant marginal cost is employed regularly in the literature. Furthermore, since the Irish automobile market is small compared to the world market, the assumption of constant marginal cost is not completely unreasonable.

As seen earlier, the operating profits of a firm \( f \) selling \( F \) different types of cars are:

\[
\Pi_f = \sum_{j=1}^{F} \left( \frac{P_j}{1 + t} Q_j - Q_j mc_j \right)
\]

\[
= \sum_{j=1}^{F} \left( \frac{P_j}{1 + t} - mc_j \right) Q_j
\]

\[
= \sum_{j=1}^{F} \left( \frac{P_j}{1 + t} - mc_j \right) M.s_j(P, x, \xi; \theta) \tag{3-9}
\]

where \( Q_j = M.s_j \), is the quantity of cars \( j \) sold, \( s_j \) is the corresponding share and \( M \) is the total market potential (inclusive of consumers opting for the outside option\(^2\)).

Assuming a Nash Equilibrium, each firm sets prices that maximize its profits given the attributes of its products and the prices and attributes of competing products. Any product \( j \) produced by firm \( f \) will have a price \( P_j \), which satisfies the following FOC

\[
\sum_{r \in F_f} \left( \frac{P_r}{1 + t} - mc_r \right) \frac{\partial s_r}{\partial P_j} + \frac{s_j(P, x, \xi; \theta)}{1 + t} = 0 \tag{3-10}
\]

Where \( Q_r = M.s_r \), \( F_f \) is the set of cars produced by firm \( f \). Therefore \( \frac{\partial Q_r}{\partial P_j} = M. \frac{\partial s_r}{\partial P_j} \) which is why \( M \) drops out of the above equation. This formula is simply the derivative of the profit expression (3-9) with respect to price \( j \).

\(^2\) The 'outside option' could either be buying second hand cars or deciding not to buy a car at all.
Hence as shown below using our demand parameters to get $\frac{\partial \delta_i}{\partial P_j}$, we can solve the $r$ first order conditions for each firm to extract the mark-up terms, $(P_i / (1 + t)) - mc_i$.  

$$\ln \left( \frac{P}{1 + t} - \left( \frac{P}{1 + t} - mc \right) \right) = w \gamma + \nu$$

Which can be rewritten as,

$$\ln \left( \frac{P}{1 + t} - \left( \Omega^{-1} \frac{s}{1 + t} \right) \right) = w \gamma + \nu$$

where $\Omega$ is a non singular matrix defined through the element by element product of the ownership structure matrix, $F$, and the gradient matrix of share with respect to prices, $Gr$:

$$\Omega = \begin{pmatrix} \frac{\partial \delta_1}{\partial P_1} & \cdots & \frac{\partial \delta_J}{\partial P_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial \delta_1}{\partial P_J} & \cdots & \frac{\partial \delta_J}{\partial P_J} \end{pmatrix} \times \begin{pmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1 \end{pmatrix} = Gr \times F$$

where, assuming $J$ products are marketed, the second matrix, $F$, is a $J \times J$ block rectangular array whose $(n,m)$ element, corresponding to row $n$ and column $m$, will equal to 1 when the product $n$ and product $M$ belong to the same profit maximizing entity. This element will be zero otherwise. It is through this second matrix that we are able to recreate the competitive conduct we want to test$^{22}$. For instance in the case of a market where all firms collude, all the elements of the ownership matrix will equal to 1 reflecting the idea that firms behave as if they where owned by a monopolistic entity. On the other hand a market where all profit maximizing firms offer only one product, the matrix will be represented by the identity matrix. In this paper we will also test intermediate scenarios falling in between these 2 extremes (Bertrand behaviour with multi product firms, market segment collusive behaviour, specific importers colluding). This may be done through the menu or conjectural variation parameters approaches which we discuss in section d.

---

$22$ See Appendix 3.2 for details on how to calculate the derivative $\frac{\partial \delta_i}{\partial P_j}$ with the nested logit.

$23$ In the case of collusion the entity does not necessarily correspond to the producing firm but rather indicates the set of firms colluding.
3.2.3 Modelling Demand

As seen above, the first order derivatives of quantities with respect to price $\frac{\partial Q_j}{\partial P_k}$ are a key input for analysing market conduct, thus the need for a suitable demand system able to infer these derivatives. As explained in Berry (1994), one might be tempted to consider the following model:

$$\ln(Q_j) = \alpha_j + \sum_k \eta_{jk} \ln(P_k) + \varepsilon_j$$

Without further thoughts we could consider the above specification very convenient since $\frac{\partial Q_j}{\partial P_k} = \eta_{jk} \left( \frac{Q_j}{P_k} \right)$ and $\eta_{jk}$ is the elasticity of good $j$ with respect to the price of good $k$.

However the cross sectional structure of our data forbids such choice. Directly modelling quantities through prices as in (3-14) is often problematic since a market with $n$ products would require the estimation of $n^2$ estimates to capture both own and cross elasticities. Thus in a market like car manufacturing where 827 different car models are made available to Irish motorists, we easily foresee the impossibility of getting 683,929 estimates. Authors like Hausman have circumvented the issue by grouping the products based on a priori knowledge and imposing symmetry restrictions on the cross elasticities. However as highlighted by Berry (1994) in many instances these choices will be arbitrary and economic theory will provide little guidance. Furthermore, even if one has access to several time periods of data a suitable statistical identification can only exist provided there is enough price variation over time. Hence using the multiplicative model to uncover $\frac{\partial Q_j}{\partial P_k}$ is not practical in a differentiated goods industry with many products since the researcher will quickly run out of degrees of freedom.

A more practical alternative is to build some structure on the demand problem based on assumptions regarding consumers’ utility specification. To do so we use the discrete choice framework whereby consumer $i$ will buy product $j$ if product $j$ is associated with the largest utility $u_{ij}$.

$$u_{ij} = \delta_{ij} + \varepsilon_{ij}$$

---

24 We observe prices and quantities sold annually for 824 cars but over a single period.

25 827².
where $\delta_y$ is known by the researcher up to some parameters and an unknown part $\epsilon_y$ treated as random. Unlike $\delta_y$ the random tastes $\epsilon_y$ are unobserved. Hence we can only infer the probability of purchase of product $j$ given the assumptions made on the distribution of these random tastes both across consumers and products.

Berry’s (1994) framework is both elegant and practical. Since the empirical model is routed into consumer utility it can be estimated with aggregate market level data where, by definition, we do not observe data on individual consumers. This is achieved by making specific assumptions about the distribution of $\epsilon_y$. Following Train (2003), we present these assumptions along with the relevant algebra.

Consider consumer $i$’s probability of purchasing product $j$ assuming that random tastes follow a double exponential distribution, the probability of purchasing product $j$ will be given by:

$$P_y = \Pr(\delta_y + \epsilon_y > \delta_{ik} + \epsilon_{ik} \quad \forall k \neq j) \quad 3-16$$

$$P_y = \Pr(\epsilon_{ik} < \delta_y + \epsilon_y - \delta_{ik} \quad \forall k \neq j) \quad 3-17$$

If $\epsilon_y$ is considered known, this expression is the cumulative distribution for each $\epsilon_{ik}$ evaluated at $\delta_y + \epsilon_y - \delta_{ik}$. If we assume that $\epsilon_{ik}$ follow a double exponential distribution and that $\epsilon_y$ is given, the cumulative distribution in 3-17 is given by $e^{-e^{-(\delta_y + \epsilon_y - \delta_{ik})}}$.

Furthermore if we assume that the $\epsilon$ are independent, this cumulative distribution over all $j \neq k$ is

$$P_y \mid \epsilon_{ij} = \prod_{j \neq k} e^{-e^{-(\delta_y + \epsilon_y - \delta_{ik})}} \quad 3-18$$

But since $\epsilon_y$ is not given, the choice probability is expressed as a weighted average of the above:

$$P_y = \int_{\epsilon_y = -\infty}^{+\infty} \prod_{j \neq k} e^{-e^{-(\delta_y + \epsilon_y - \delta_{ik})}} e^{-\epsilon_y} e^{-\epsilon_y} d\epsilon_y \quad 3-19$$

Following some algebraic manipulations we get$^{26}$

$^{26}$ See Train (2003) p 78.
The expression above does not consider an outside alternative explicitly, when incorporating it and normalising its utility to zero:

\[ P_y = \frac{e^{\delta_y}}{\sum_j e^{\delta_j}} \]

The link to aggregate market shares is implemented by following a process similar to the principle of sample enumeration. Train (2003) explains that an estimate of the total number of decision makers, in the population who choose alternative \( j \), labelled \( Q_j \), can be seen as the sum of the individual probabilities when the consumers are assumed to be pooled out of a random sample:

\[ Q_j = \sum_{n=1}^M P_y \]

leading to the following market share equation

\[ S_j = \frac{Q_j}{M} = \frac{\sum_{n=1}^M P_y}{M} \]

Since in our case we do not observe individual data we simply assume that we are observing the outcome of the above process whereby the market share of product \( j \) is equal to the average probability across \( M \) consumers. This setting presents some benefits since the product with the largest market share will be mapped to the product with the highest probability of purchase while the opposite will hold true for the product with the smallest market share.

We now focus on Berry’s framework applied to the simple logit model. The key difference with the previous utility equation in (3-15) relates to the assumption that the mean market utility for each product, \( \delta_j \), can be expressed as a linear form:

\[ u_{ij} = \delta_j + \epsilon_{ij} \]

\[ \delta_j = x_j \beta + \alpha y_j + \xi_j \]

---

27 This normalization bears no consequences since the utility framework is scale invariant, hence the utility of the \( j \) remaining product will adjust accordingly.

28 This assumption allows us to use a simple average, if one uses a stratified sample then relevant weights need to be applied to the formula.
In which $x_j$ are the observed characteristics of product $j$, $p_j$ is price and $\xi_j$ are the overall impact on utility from characteristics unobserved to the researcher. As before we assume that $\xi_j$ are following a double exponential distribution across both products and consumers. Thus the probability of purchase of individual $i$ will be equal to the probability of purchase of individual $j$:

$$P_y = P_y = \frac{e^{\xi_i}}{1 + \sum_k e^{\xi_k}} \quad (3-26)$$

Using the sample enumeration principle we derive $Q_i$:

$$Q_j = \sum_{i=1}^M P_y = \frac{\sum_i e^{\xi_i}}{\sum_k e^{\xi_k}} = M \frac{\sum_i e^{\xi_i}}{\sum_k e^{\xi_k}} \quad (3-27)$$

Leading to the following market share

$$S_j = \frac{Q_j}{M} = \frac{e^{\xi_j}}{\sum_k e^{\xi_k}} \quad (3-28)$$

While seductive the logit model might nonetheless be inadequate in some markets due to the substitution patterns it imposes. These limitations can be seen when looking at the cross elasticity.

$$\mu_{ij} = \frac{\partial Q_r}{\partial p_j} \frac{p_j}{Q_r} = \frac{\partial S_r}{\partial p_j} \frac{p_j}{S_r} \quad (3-29)$$

Assuming the average utility across consumer, $\delta_j$, is linear in price such that:

$$\frac{\partial \delta_j}{\partial p_j} = \alpha \quad (3-30)$$

We have

$$\frac{\partial S_r}{\partial p_j} = \frac{\partial S_r}{\partial \delta_j} \frac{\partial \delta_j}{\partial p_j} = -S_r S_j \alpha \quad (3-31)$$

---

29 In the previous and more general example assuming such distribution across product only was sufficient since we only look at the case of one consumer.

30 This point was first raised by Chipman (1960) and Debreu (1960).
Which gives us

\[ \mu_j = -S_j \cdot p_j \alpha \]  

This formula however constrains the cross elasticity to be the same for any product \( r \) since \( r \) does not enter the formula. We can see it through an example. Let’s assume that we are interested in simulating the change in numbers of BMW buyers vs. Skoda buyers following a price increase in Mercedes. Assume also that both BMW and Skoda receive the same market share before the price increase. This model assumes that the same numbers of consumers will switch from Mercedes to Skoda and from Mercedes to BMW\(^{31}\). This result raises scepticism when we factor in that both Mercedes and BMW vehicles are more targeted towards the same type of consumers while Skoda is aimed at a more price sensitive audience. Hence one would expect the number of consumers switching from Mercedes to BMW to be higher than the number of consumers switching from Mercedes to Skoda.\(^{32}\) To get around this IIA property specific to the logit model, we must use a functional form that will be flexible enough to reach more intuitive patterns. This is achieved through the Nested Logit which, following Berry (1994),\(^ {33} \) is related to the following consumer \( i \)'s utility for product \( j \):

\[ u_{ij} = \delta_j + \zeta_{ig} + (1 - \sigma) \epsilon_{ij} \]  

we reproduce what we did for the simple logit model and set \( \delta_j = x_j / \beta + \alpha p_j + \xi_j \) as the mean utility of product \( j \) averaged across consumers. Like the simple logit, the nested logit is convenient for its tractability since it has analytical solutions when aggregating over consumers.

The difference between the logit and the nested logit resides in the presence of the variable \( \zeta \), which is common to all products in group \( g \) and has a distribution depending on \( \sigma, 0 \leq \sigma < 1 \). Sigma can be considered a scaling factor reflecting the relative importance of \( \epsilon_{ij} \) compared to \( \zeta_{ig} \), the marginal utility associated with a specific group of products which we call a segment.\(^ {34} \) We will see that when \( \sigma = 0 \) we are back to the simple logit utility specification while when \( \sigma \) rises to 1 the correlation between product belonging to the same segment increases. Although we can intuitively feel it by observing the relative rising impact of \( \zeta_{ig} \)

\(^{31}\) This pattern of substitution is a manifestation of what is called the Independence of Irrelevant Alternative, also known as IIA property.  

\(^{32}\) The same logic can be applied to the cross elasticity between a third product 2 other very different products yet receiving the same share (e.g. a large family and a sport coupe).  

\(^{33}\) See also Cardell (1991) McFadden (1978).  

\(^{34}\) We will see in the next part how to estimate it empirically.
compared to the individual specific tastes $\varepsilon_{ij}$ when $\sigma$ vanishes, on the other hand when $\sigma=1$, the individual specific tastes vanishes relative to the segment specific tastes. This within segment correlation is likely to be exacerbated through the expected similarity between $\delta$ from 2 different products since cars belonging to the same segments usually have similar characteristics. This correlation can be made more explicit if we consider $\zeta_{ig}+(1-\sigma)\varepsilon_{ij}$ like a composite error term. We will now have a closer view on the distributions leading to the nested logit.

As explained by Train(2003), the nested logit is obtained by assuming that the vector $\varepsilon_i = \{\varepsilon_{i1}, \ldots, \varepsilon_{ij}\}$ has the following cumulative General Extreme Value distribution:

$$\exp \left( \sum_{g=1}^{G} \left( \sum_{j \in T_g} e^{-\varepsilon_{ij}/(1-\sigma)} \right)^{(1-\sigma)} \right)$$

It is a generalization of the distribution that gives rise to the logit model. However while the marginal distribution of each $\varepsilon_{ij}$ is univariate extreme value, the $\varepsilon_{ij}$'s belonging to the same group will be correlated. As explained earlier the parameter $\sigma$ is a measure of correlation in the sense that as $\sigma$ drops to zero there will be a large degree of independence between the unexplained utility $\varepsilon_{ij}$ from the alternatives in group $g$. When $\sigma=0$, we are back to the simple logit case. On the other hand as $\sigma$ rises to 1 the random part of utility from alternatives belonging to the same group becomes more and more correlated. Due to such features the nested logit is able to diminish the influence of the IIA property. Through $\zeta$, a consumer's utility receives a common shock for all the products belonging to the chosen segment. Consequently this consumer is more likely to switch to another product belonging to the same segment if the product’s price of interest is to be increased. Nonetheless the nested logit only partially address the IIA, since product substitutions within a segment are still affected by the IIA.\(^{35}\)

Because $\zeta+(1-\sigma)\varepsilon$ has an extreme value distribution McFadden (1978) shows that when integrating the utility over all consumers we obtain the following probability of choosing product $j$.

\(^{35}\) This is made explicit through the cross elasticities of 2 products belonging to the same segment. The associated formula is exposed in appendix.
\[ S_j = \frac{e^{\delta_j/(1-\sigma)}}{D_g \left( \sum_g D_g^{1-\sigma} \right)} \quad \text{where} \quad D_g = \sum \left( e^{\delta_j/(1-\sigma)} \right) \]

\( G_g \) denotes the set of automobiles of type \( g \), and \( 1 \leq \sigma < 0 \) is an additional parameter to be estimated; as already conveyed, when \( \sigma = 0 \), the cross elasticities among products do not depend on the classification; in this case, the simple logit model is appropriate. When \( \sigma > 0 \), there is a higher degree of substitution among cars belonging to the same group than among cars from different groups. If \( \sigma \) approaches one, the cross elasticity between any two cars that belong to different groups approaches zero.

Formula (3-35) has more intuitive appeal when expressing it as the product of a marginal and a conditional probability:

\[ S_j = S_{j/g} S_g \]

\[ S_g = \frac{\left( \sum e^{\delta_j/(1-\sigma)} \right)^{(1-\sigma)}}{\sum \left( \sum e^{\delta_j/(1-\sigma)} \right)^{(1-\sigma)}} = \frac{D_g^{(1-\sigma)}}{\sum D_g^{(1-\sigma)}} \]

\[ S_{j/g} = \frac{e^{\delta_j/(1-\sigma)}}{\sum e^{\delta_j/(1-\sigma)}} = \frac{e^{\delta_j/(1-\sigma)}}{D_g} \]

To estimate the model parameters from aggregate data we follow Berry (1994) where the utility of the outside option \( \delta_g \) is scaled to zero. Following (3-35) the probability of the outside option is given as

\[ S_o = \frac{e^{\delta_o/(1-\sigma)}}{D_o^{(1-\sigma)}} = \frac{e^{\delta_o/(1-\sigma)}}{\sum \left( \sum e^{\delta_j/(1-\sigma)} \right)^{(1-\sigma)}} = \frac{1}{\sum D_g^{(1-\sigma)}} \]

As for the simple logit we take the logs of market shares

\[ \ln(S_j) - \ln(S_o) = \frac{\delta_j}{1-\sigma} - \sigma \ln(D_g) \]

Solving \( S_g \) formula for \( \ln(D_g) \) in (3-37) and taking the logs of market shares as above,

\[ \ln(S_g) = (1-\sigma) \ln(D_g) + \ln \left( \sum D_g^{(1-\sigma)} \right)^{-1} \]
\[
\ln(D_g) = \frac{\ln(S_{jg}) - \ln(S_0)}{(1 - \sigma)}
\]

Substituting this expression into (3.40):

\[
\ln(S_j) - \ln(S_0) = \delta_j/(1 - \sigma) - (\sigma/(1 - \sigma)). [\ln(S_{jg})-\ln(S_0)]
\]

\[
\ln(S_j) - \ln(S_0) + (\sigma/(1 - \sigma)) [\ln(S_{jg})-\ln(S_0)] = \delta_j/(1 - \sigma)
\]

\[
\ln(S_j) - \ln(S_0) = \delta_j + \sigma \ln \left( \frac{S_{jg}}{S_j} \right)
\]

\[
\ln(S_j) - \ln(S_0) = \delta_j + \sigma \ln(S_{jg})
\]

Where \( S_{jg} \) is the share of product \( j \) within group \( g \) defined in (3.35) and \( S_0 \) is the share of consumers choosing not to purchase a new car.

We estimate \( S_0 \) based on the size of second hand car market which we get from our data set, hence we consider the potential market as being based on consumers buying new cars and second hand cars. We could extent this market by also including public transport users and cyclists who do not own a car if we had the data available but research has shown that the size of the outside market mostly influences the intercept and therefore will not affect our analyses since our interest is on \( \frac{\partial Q_j}{\partial P_k} = M(\frac{\Delta S_j}{\Delta P_k}) \) where \( M \) denotes the potential market size.

Keeping in mind that \( \delta_j = x_j \beta + \alpha p_j + \xi_j \)

\[
\ln(S_j) - \ln(S_0) = x_j \beta + \alpha p_j + \xi_j + \sigma \ln(S_{jg})
\]

\[
= \delta_j + \sigma \ln(S_{jg})
\]

Berry (1994) defines \( \xi_j \) as the hard to quantify measure related to product unobserved quality, prestige or image. Because these factors are expected to be correlated with price and share within segment \( g \), we face endogeneity issues and proper instrumentation will be required. Hence we can estimate \( \alpha, \beta \) and \( \sigma \) through GMM as explained in section 3.3.

3.2.4 **Eliciting the most likely Competitive Behaviour**

3.2.4.1 **The Conjectural Variations Framework**

Rather than being specific to a given collusive scenario, the CV framework elicits the degree of collusiveness prevailing on the market. The idea behind the CV method is to capture the distance between a Perfect Bertrand-Nash equilibrium and the model being empirically tested.
Even though it is quite helpful when one is interested in ranking markets by order of competitiveness, it does not necessarily lead to clear cut conclusions hence it can be considered of limited value to practitioners, unless they have recognized benchmark values. Furthermore its implementation is not straightforward. Discussions of this methodology are found in Nevo (1998) and Bresnahan (1989), while both the Sudhir (2001) and Brenkers and Verboven (2006) use it empirically in the automotive market.

3.2.4.2 The Menu Framework

As we have just seen, through the assumption that observed market prices are the outcome of Bertrand-Nash equilibrium behaviour, testing various market behaviours is equivalent to testing different Bertrand-Nash equilibrium formations.

Whether a firm or a cartel, the profit maximizing “entity” will behave strategically and take into account the cross price elasticities of car models falling under its management.

As mentioned earlier, the ownership matrix entering $\Omega$ is the key element we interact with to implement various competitive scenarios. These scenarios can then be compared in terms of fit based on the sum of residuals associated with each model. This approach is followed by authors like Sudhir (2001) who then choose the conduct most reflecting the data. This tactic can be of limited support when the fit is quite similar across specifica..."
Where \( J_1 \) and \( J_2 \) are the corresponding minimized values of the objective function, \( j_{11} \) and \( j_{12} \) are the individual observation values of the objective function evaluated at the minimum and \( N \) the total number of observations. This statistic is expected to follow a standard normal distribution. Note that this test is also directional, in other words a positive statistic will suggest that model 2 is less appropriate than model 1. Another desirable property mentioned by Gasmi and Vuong (1992) is that none of the models need to be correctly specified. The Vuong test is based on the likelihood ratio (LR) principle, and is designed to test the null hypothesis that two competing models adjust equally well the data versus the alternative hypothesis that one model fits better. This test will allow us to determine which of the underlying behaviours most adequately explain the data.

### 3.3 Empirical Approach

In this part we present the technicalities underpinning the GMM estimation which we use to simultaneously uncover the demand (\( \beta, \alpha, \xi, \sigma \)) and the marginal impact of the product characteristics (\( \gamma, \nu \)) on marginal costs.

#### 3.3.1 Simultaneous General Method of Moments

Isolating product markups requires that we estimate the simultaneous system represented by equations (3-47) and (3-12):

\[
\ln(S_j) - \ln(S_o) = \delta_j + \alpha \ln(S_{j^*}) + \xi_j
\]

\[
\ln \left( \frac{p_j}{1 + t_j} \right) - \left( \Omega^{-1}(\alpha, \sigma) \right) = w_j\gamma + \nu_j
\]

To benefit from efficiency gains these 2 equations are estimated simultaneously. Nonetheless this is not straightforward since due to market dynamics between suppliers and consumers, \( \xi_j \) and \( \nu_j \) are likely to be correlated with price and within segment share. Hence we must deal with an endogeneity problem. We use the gmm method to address the issue. We deploy the instruments suggested by Berry (1994) for the nested logit. Namely for the demand equation (3-49) we take the sum of other cars' characteristics belonging to the same firms and marketed within the same segment as product \( j \) while on the cost side we take the sum of all other cars produced by rival firms and competing on the same segment. Intuitively, these

---

37 The intuition being that Model 2 tends to push that statistic upwards in the positive domain indicating a relatively lower congruence with the identifying assumptions compared to model 1. In other words \( J_1 \) can be considered as systematically lower than \( J_2 \).

38 representing unobserved quality and cost respectively.
instruments incorporate frictions between firms. Since we would expect products closely
located to each to compete more intensely, the associated markups will be relatively lower for
the closely located products than for products positioned in less contested area of the product
space. Hence these instruments will have an effect on price but will not be related to the
unobserved product quality, $\xi$. Indeed we have seen that consumers’ product utility for $j$ is
only based on the characteristics of $j$. Likewise $S_{jn}$ needs to be instrumented since higher $\xi$ are
expected to be associated with larger $S_{jn}$. Since the segment where more competing products
are available will tend to be associated with smaller $S_{jn}$ the instruments described above are
also relevant for $S_{jn}$. Given that (3-33) excludes any characteristics from other products than $j$,
the identification is valid.

To deal with the endogeneity of $\nu_j$, we need to find instruments not correlated with the
unobserved marginal $\nu_j$ costs and yet able to shift demand for $j$ to ensure identification. The
denominator of the nested logit Formula (3-35) makes it clear that other cars’ characteristics
will influence the share of product $j$, while there is no reason to believe that other cars
characteristics will impact on the marginal cost of $j$. Hence the equilibrium instruments used
to identify the mean utility will also be valid cost instruments since they will be uncorrelated
to unobserved costs $\nu_j$, yet they are expected to influence the markup that can be charged on
car $j$, $\left(\Omega^{-1} s_j\right)/(1 + t_j)$ since these instruments will be a reflection of the number of competing
cars with similar characteristics and located in the same segment as $j$. However to avoid
singularity issues, we discriminate between characteristic from cars within segment $g$ ($j \in g$)
produced by competitors and the characteristics of other cars produced by firm $j$ within
segment $g$. Indeed while competing cars will create a downward pressure on markups the
firm producing $j$ can charge, other cars from firm $j$ in segment $g$ is expected to ease up this
pressure. Therefore we will use the average of each characteristic from other cars, produced
by the same firm manufacturing car $j$ in the same segment $g$, as utility side instrument while
the average characteristics of competing finns in the same segment will be used to identify
the pricing equation.

Assuming that observed characteristics are exogenous we build the following objective
function:

$$
\begin{bmatrix}
\xi \\
\nu
\end{bmatrix}
Z W^{-1} Z^t\begin{bmatrix}
\xi \\
\nu
\end{bmatrix}
$$

Where $\xi$ and $\nu$ are the unobserved demand and cost vectors defined in (3-49) and (3-50),
which we interact with $Z$, a partitioned matrix containing the relevant set of instruments
$Z_A$ characteristics of car $j$ and the sum of the characteristics of other within segment cars
produced by the firm) and $Z_j$ (Characteristics of car $j$ and sum of characteristics of other within segment cars produced by the competitors):

$$Z = \begin{bmatrix} Z_d \\ Z_s \end{bmatrix}$$  \hspace{1cm} 3-52

For the weighting matrix we use Hansen's finding on optimality and set:

$$W = Z' E(uu')Z$$  \hspace{1cm} 3-53

With $u = \begin{bmatrix} \xi \\ \eta \end{bmatrix}$. Assuming heteroscedasticity $E(uu')$ is therefore estimated through the following diagonal matrix:

$$E(uu') = \begin{bmatrix} \sigma_1^2 & 0 & \cdots & 0 \\ 0 & \sigma_2^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_n^2 \end{bmatrix}$$  \hspace{1cm} 3-54

Following results of Hansen (1996) this is estimated through a 2 stage process since Hansen did not report any obvious gain from an iterative estimation. In the first stage process we assume homoscedasticity and set $E(uu') = \Omega^{*}$, where we can drop $\sigma^2$ since it will not affect our parameters. We can then extract the corresponding vector $u$ which is used to estimate $W$

\[\text{Stage 1: } gmm_1(\theta) = \left[ \xi_1 \\ \eta_1 \right] Z[Z'Z]^{-1}Z'\left[ \xi_1 \\ \eta_1 \right] \]

\[\text{Stage 2: } gmm_2(\theta) = \left[ \xi \\ \eta \right] Z[Z'[Z'Z]^{-1}Z']^{-1}Z'\left[ \xi \\ \eta \right] \]

As suggested in Berry (1994) and BLP (1995) we can alleviate the computational burden by splitting linear from non linear parameters at each stage. We have $\theta = \{\alpha, \beta, \eta, \xi\}$ where $\beta$ are the linear parameters corresponding to the characteristics entering the demand & supply side while $\alpha$ and $\sigma$ are parameters corresponding to the price and within segment share and entering demand and supply. We now solve the objective function for the linear parameters $\beta$

Setting first vector $Y_{(\alpha, \sigma)}$ to

$$\begin{bmatrix} \ln(S_j) - \ln(S_o) - \alpha P_j - \sigma \ln(S_{R_j}) \\ \ln \left( \frac{P_j}{1 + t_j} - \left( \frac{\Omega^{*}_{(\sigma, \sigma)} S_j}{1 + t_j} \right) \right) \end{bmatrix}$$  \hspace{1cm} 3-57
We have:

\[
\beta = [X'Z(Z'WZ)^{-1}Z'X]^{-1}[X'Z(Z'WZ)^{-1}Z'Y_{(\alpha, \sigma)}]
\]  

Based on the above we can express the residuals as

\[
\begin{bmatrix} \xi \\ u \end{bmatrix} = Y_{(\alpha, \sigma)} - X \beta, \text{ which we substitute back into (3-55) and (3-56)}.
\]

### 3.3.2 The Optimization Algorithm

To solve for the non linear parameters minimizing (3-55) and (3-56) we must use a recursive algorithm. Most of the existing literature has used the derivative free simplex method; here we incorporate the information contained through the first order derivatives of the gmm function. We also constrain the feasible domain of the objective function in order to ensure that the implied marginal costs are positive.

Because Sequential Quadratic Algorithm has proven to be a robust method, this is the method we implement. To optimize the search algorithm we incorporate the gradient of the gmm function defined in (3-56)\(^3\):

\[
\frac{\partial \text{gmm}_d(\alpha, \sigma)}{\partial \alpha} = 2Z_d \frac{\partial u_{d(\alpha, \sigma)}}{\partial \alpha} [Z_d' [E(u_d'u_d')]Z_d]^{-1}Z_d'u_{d(\alpha, \sigma)}
\]

\[
\frac{\partial \text{gmm}_s(\alpha, \sigma)}{\partial \alpha} = 2Z_s \frac{\partial u_{s(\alpha, \sigma)}}{\partial \alpha} [Z_s' [E(u_s'u_s')]Z_s]^{-1}Z_s'u_{s(\alpha, \sigma)}
\]

\[
\frac{\partial \text{gmm}_d(\alpha, \sigma)}{\partial \sigma} = 2Z_d \frac{\partial u_{d(\alpha, \sigma)}}{\partial \sigma} [Z_d' [E(u_d'u_d')]Z_d]^{-1}Z_d'u_{d(\alpha, \sigma)}
\]

\[
\frac{\partial \text{gmm}_s(\alpha, \sigma)}{\partial \sigma} = 2Z_s \frac{\partial u_{s(\alpha, \sigma)}}{\partial \sigma} [Z_s' [E(u_s'u_s')]Z_s]^{-1}Z_s'u_{s(\alpha, \sigma)}
\]

### 3.4 Data and Industry Overview

In this part we simply introduce our data set and take the opportunity to provide the reader with an industry overview.

To conduct our analyses we collated data from multiple sources as described in Chapter 1. The same dataset was used in Mariuzzo, Walsh and Van Parys (2009). Our data on the new car market in Ireland in 2003 shows purchases of 133,000 automobiles, grossing 3.3 billion Euro in sales, highlighting the importance of the industry.

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\(^3\) See appendix for details.
We use data on product characteristics which we gathered through various specialized press magazine and web sites. Product characteristics for which we have data include the size of the engine, the vehicle dimensions (height, width and length), the weight, the fuel efficiency (in miles per gallon), performance related measures (horsepower and acceleration), body type (hatch, saloon, estate, convertible or SUV), model lifestage (year when the model was launched and year when the model is expected to be phased out), a dummy for whether the car has automatic transmission or diesel based combustion.

As in BLP(1995) the price variable is the list retail price as opposed to transaction prices. Since these retail prices are also inclusive of tax we will have to deflate them by the appropriate tax rate in order to use these variables in our pricing equation. Hence we build the following deflator $t$:

$$t = (1 + \text{VAT}) \times ((1 + \text{VRT}_1) \times \text{cc}_{1400} + (1 + \text{VRT}_2) \times \text{cc}_{1900} + (1 + \text{VRT}_3) \times (1 - \text{cc}_{1400} - \text{cc}_{1900}))$$

where $\text{VAT}$ is the current value added tax rate (21 per cent), $\text{cc}_{1400}$ is a dummy equal to 1 if the engine size is below 1.4 litres, $\text{cc}_{1900}$ is another dummy indicating whether the car’s engine is between 1.4 litres and 1.9 litres, while the last bracketed term indicate all cars with an engine capacity larger than 1.9 litres. Finally $\text{VRT}_1$, $\text{VRT}_2$ and $\text{VRT}_3$ are the corresponding Vehicles Registration Tax rates for each engine size category (i.e. 22.5, 25 and 30 per cent respectively). The data set includes this information on all models marketed in 2003, totalling 1277 observations, however upon cleaning and grouping models with very similar characteristics we are left with 827 models. Each of these models falls into one of the 7 following market segments as specified by industry publications:

- **City/subcompact** (e.g. Peugeot 206, Ford Fiesta)
- **Compact** (e.g. Audi A4, Honda Civic, Ford Focus)
- **Medium** (e.g. VW Passat, Opel Vectra, Nissan Primera)
- **Executive** (e.g. Mercedes C Class, Volvo S40, BMW 500)
- **Off Roads, SUV, 4X4** (e.g. Honda CRv, Land Rover)
- **Convertible & Coupe** (e.g. Toyota MR, Audi TT)
- **Multi Purpose Vehicles** (e.g. Mistubishi Space Wagon, Renault Espace).

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40 See appendix.

41 We could create a "% of life variable" and create a quadratic, this variable expected to show negative in cost due to "learning by doing", and negative hyperbolic with slow take up and rapid decrease reflecting network effect and desire to get a new model which can resale better on the second hand market.

42 A better option would have been transaction price but accessing such data is difficult since it would have to be done at an individual level. The department of revenue was not forthcoming in releasing such data as it would potentially infringe on consumers' confidentiality rights.
Table 3.1 identifies the cheapest and dearest car in each segment. In Ireland the cheapest car available in 2003 was the Fiat Panda, which was worth €10,995, while the most expensive was the Mercedes CL Class marketed at €200,950.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Make</th>
<th>Model</th>
<th>Price</th>
<th>MPG</th>
<th>HP</th>
<th>0-100 km/h</th>
<th>cc</th>
<th>tax</th>
</tr>
</thead>
<tbody>
<tr>
<td>City</td>
<td>FIAT</td>
<td>PANDA</td>
<td>€10,995</td>
<td>49.5</td>
<td>54</td>
<td>14.4</td>
<td>1108</td>
<td>€216</td>
</tr>
<tr>
<td>City</td>
<td>SMART</td>
<td>SPORTSER</td>
<td>€28,995</td>
<td>55.4</td>
<td>80</td>
<td>10.9</td>
<td>698</td>
<td>€144</td>
</tr>
<tr>
<td>Compact</td>
<td>KIA</td>
<td>RIO</td>
<td>€12,995</td>
<td>39.8</td>
<td>75</td>
<td>12.9</td>
<td>1343</td>
<td>€278</td>
</tr>
<tr>
<td>Compact</td>
<td>ALFA ROMEO</td>
<td>147</td>
<td>€43,500</td>
<td>23</td>
<td>250</td>
<td>6.1</td>
<td>3179</td>
<td>€1,279</td>
</tr>
<tr>
<td>Medium</td>
<td>MITSUBISHI</td>
<td>CARISMA</td>
<td>€18,332</td>
<td>41.5</td>
<td>84</td>
<td>13.4</td>
<td>1297</td>
<td>€259</td>
</tr>
<tr>
<td>Medium</td>
<td>OPEL</td>
<td>VECTRA</td>
<td>€40,578</td>
<td>28.1</td>
<td>211</td>
<td>7.5</td>
<td>3175</td>
<td>€1,279</td>
</tr>
<tr>
<td>Exec</td>
<td>VOLVO</td>
<td>S40</td>
<td>€25,900</td>
<td>33.2</td>
<td>109</td>
<td>12</td>
<td>1600</td>
<td>€372</td>
</tr>
<tr>
<td>Exec</td>
<td>MERCEDES</td>
<td>S CLS</td>
<td>€200,200</td>
<td>21.1</td>
<td>389</td>
<td>6.3</td>
<td>5513</td>
<td>€1,279</td>
</tr>
<tr>
<td>CV/Coupe</td>
<td>HYUNDAI</td>
<td>COUPE</td>
<td>€24,745</td>
<td>36.7</td>
<td>116</td>
<td>11.2</td>
<td>1599</td>
<td>€372</td>
</tr>
<tr>
<td>CV/Coupe</td>
<td>MERCEDES</td>
<td>CL CLS</td>
<td>€200,950</td>
<td>21.7</td>
<td>355</td>
<td>6</td>
<td>5513</td>
<td>€1,279</td>
</tr>
<tr>
<td>4x4/SUV</td>
<td>SUZUKI</td>
<td>JIMNY</td>
<td>€16,610</td>
<td>34.4</td>
<td>79</td>
<td>16</td>
<td>1328</td>
<td>€259</td>
</tr>
<tr>
<td>4x4/SUV</td>
<td>PORSCHE</td>
<td>CAYENNE</td>
<td>€162,070</td>
<td>18</td>
<td>450</td>
<td>5.4</td>
<td>4511</td>
<td>€1,279</td>
</tr>
<tr>
<td>MPV</td>
<td>SUZUKI</td>
<td>WAGON</td>
<td>€11,995</td>
<td>51.4</td>
<td>53</td>
<td>16</td>
<td>993</td>
<td>€144</td>
</tr>
<tr>
<td>MPV</td>
<td>CHRYSLER</td>
<td>VOYAGER</td>
<td>€59,145</td>
<td>22.2</td>
<td>180</td>
<td>11.9</td>
<td>3301</td>
<td>€1,279</td>
</tr>
</tbody>
</table>
In Table 3.2, we also see that 4x4, Convertibles and Coupe cars are amongst the least fuel efficient while, on the other hand, City/Compact cars are the most fuel efficient. Unsurprisingly small engine sizes also tend to be found in these segments. A smaller engine allows the car owner to benefit from lowest ownership cost due to both lower fuel consumption and lower taxation. Consequently one would expect consumers from the later segment to be more price sensitive than consumers deciding to buy an executive car or a coupe.43

<table>
<thead>
<tr>
<th>Segment</th>
<th>Average Mpg</th>
<th>Average hp</th>
<th>Average accel (sec)</th>
<th>% of model with auto gear box</th>
<th>No of Years before Replace</th>
<th>No of Years since Launch</th>
<th>No of Models</th>
</tr>
</thead>
<tbody>
<tr>
<td>4x4</td>
<td>28.36</td>
<td>163</td>
<td>11.86</td>
<td>18%</td>
<td>4.18</td>
<td>2.30</td>
<td>61</td>
</tr>
<tr>
<td>City</td>
<td>47.52</td>
<td>76</td>
<td>13.82</td>
<td>6%</td>
<td>4.83</td>
<td>1.81</td>
<td>135</td>
</tr>
<tr>
<td>Compact</td>
<td>43.94</td>
<td>105</td>
<td>11.65</td>
<td>4%</td>
<td>2.99</td>
<td>3.07</td>
<td>188</td>
</tr>
<tr>
<td>Cv/Coupe</td>
<td>29.66</td>
<td>218</td>
<td>7.89</td>
<td>16%</td>
<td>4.68</td>
<td>2.66</td>
<td>44</td>
</tr>
<tr>
<td>Exec</td>
<td>34.65</td>
<td>178</td>
<td>9.38</td>
<td>16%</td>
<td>3.89</td>
<td>3.10</td>
<td>171</td>
</tr>
<tr>
<td>Medium</td>
<td>39.85</td>
<td>126</td>
<td>11.07</td>
<td>10%</td>
<td>4.05</td>
<td>2.44</td>
<td>154</td>
</tr>
<tr>
<td>Mpv</td>
<td>38.76</td>
<td>113</td>
<td>13.15</td>
<td>5%</td>
<td>3.88</td>
<td>2.27</td>
<td>74</td>
</tr>
<tr>
<td>Total</td>
<td>39.47</td>
<td>130</td>
<td>11.38</td>
<td>10%</td>
<td>3.93</td>
<td>2.60</td>
<td>827</td>
</tr>
<tr>
<td>Market</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3.3, taken from Mariuzzo, Walsh and Van Parys (2009) illustrates that the City segment is the least concentrated with the top 4 firms holding 54 per cent of the market share, while the expected share represented by the 4 largest firms across segments is 70 per cent. If Bain’s paradigm, S-C-P, holds, we would expect competition to be fiercer in the City segment, therefore expecting lower markups. On the other hand we would expect larger markups to prevail on the Executive and Convertible/Coupe segment since the joint share represented by the 4 largest firms in each segment is respectively 80 per cent and 88 per cent.

Table 3.3a: Top Four-Companies/Importer Concentration Index (Unit Sales)

<table>
<thead>
<tr>
<th>Market</th>
<th>Unit Sales</th>
<th>C4 Brands</th>
<th>C4 Importers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average (Unit Weighted)</td>
<td>133,000</td>
<td>46 %</td>
<td>57%</td>
</tr>
</tbody>
</table>

43 The functional form allowing to check this will be implemented in another revision of this paper.
Segment | % of Unit Sales by Segment | Within Segment C4 Brands | Within Segment C4 Importers
--- | --- | --- | ---
Compact (Medium) Cars | 31 | 61 | 64
City (Small) Cars | 28 | 48 | 54
Medium (Large) Cars | 20 | 58 | 74
Executive Cars | 10 | 80 | 96
Off Roads, SUV, 4X4 | 5 | 55 | 55
Multi Purpose Vehicles | 5 | 56 | 56
Convertible & Coupe | 1 | 88 | 93
Average | 100 | 64% | 70%

### 3.5 Empirical Results

Based on the above data and methodologies we now turn to our empirical results. We first comment on the estimates from the simultaneous models in (3-56). We then use the markups we inferred from \( \left( \Omega^{-1} \frac{s}{1+t} \right) \) to conduct a profit analyses. We then test for various scenarios and elicit the most likely market conduct prevailing in the industry. Finally we simulate some counter factual related to the ax transition. We use the marginal costs associated with the most likely market conduct and simulate the new price equilibriums under the tax change.

#### 3.5.1 Model Results

Because the pricing equation also depends on demand parameters we estimate demand and supply parameters simultaneously. While the procedure is more complicated, it is expected to be more efficient than a sequential estimation.

In Table 3.4 and Table 3.5 we show the demand and supply parameters regarding 5 possible competitive behaviours between firms. The “Single Product” setting assumes that firms do not account for cross cannibalization between models within their respective portfolio. This scenario is the most intense from a competition aspect. A somewhat less intense scenario but still sub-optimum from a manufacturer standpoint is “brand” profits are maximized at a brand level. The “Plc” pricing scenario goes even further by accounting for the fact that several brands are owned by the same corporation (for instance Volkswagen also owns Audi and Seat) and have the possibility to legally exert greater market power by accounting for substitution patterns across the brands within their portfolio. The “Collusion” setting reflects the worst case scenario from a consumer welfare stand...
point since all the manufacturers are coordinating prices, therefore acting like a monopoly. The "Importers" locate the collusive behaviour between 2 importers while the remaining firms behave within the legal boundaries. These scenarios are discussed in further details in section 3.5.3 where we investigate which ones best reflect our data through the use of the Vuong test. For now we focus on the quality of the parameters and we see that the characteristics estimates are correctly signed. Consumers value powerful cars that consume little fuel, and they also value cabin space (length & height). The price is significant in all five competitive settings. Curiously, while the validity of our instruments can not be rejected when we focus on demand and supply specifications individually, the single product assumption is rejected when considering the simultaneous J statistic. To some extent it is reassuring to observe such an outcome since the single product pricing behaviour would intuitively be expected to be the less realistic setting.

Table 3.4: Demand Estimates

<table>
<thead>
<tr>
<th>Variable</th>
<th>Collusion</th>
<th>Importers</th>
<th>Plc</th>
<th>Brand</th>
<th>Single Product</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Price (a)</strong></td>
<td>Coef</td>
<td>Coef</td>
<td>Coef</td>
<td>Coef</td>
<td>Coef</td>
</tr>
<tr>
<td></td>
<td>-1.54e-05</td>
<td>-1.68e-05</td>
<td>-1.66e-05</td>
<td>-1.65e-05</td>
<td>-1.37e-05</td>
</tr>
<tr>
<td><strong>Sigma</strong></td>
<td>0.97</td>
<td>0.94</td>
<td>0.93</td>
<td>0.90</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td>73.28</td>
<td>44.45</td>
<td>39.11</td>
<td>29.39</td>
<td>21.38</td>
</tr>
</tbody>
</table>

Characteristic:

- **mpg**: 0.01 | 1.74
- **Horsepower**: 0.01 | 6.67
- **Length**: 0.00 | 2.15
- **Height**: 0.01 | 1.73

<table>
<thead>
<tr>
<th>Firm Dummies</th>
<th>Not Reported</th>
<th>Not Reported</th>
<th>Not Reported</th>
<th>Not Reported</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seg: 4x4</td>
<td>-2.13</td>
<td>-2.04</td>
<td>-2.02</td>
<td>-1.95</td>
</tr>
<tr>
<td>Seg: City</td>
<td>-0.07</td>
<td>-0.05</td>
<td>-0.05</td>
<td>-0.05</td>
</tr>
<tr>
<td>Seg: MPV</td>
<td>-2.20</td>
<td>-2.14</td>
<td>-2.13</td>
<td>-2.09</td>
</tr>
<tr>
<td>Seg: Exec</td>
<td>-1.14</td>
<td>-1.10</td>
<td>-1.11</td>
<td>-1.08</td>
</tr>
<tr>
<td>Seg: Medium</td>
<td>-0.49</td>
<td>-0.48</td>
<td>-0.48</td>
<td>-0.47</td>
</tr>
<tr>
<td>Seg: CV&amp;Coupe</td>
<td>-2.79</td>
<td>-2.69</td>
<td>-2.67</td>
<td>-2.58</td>
</tr>
<tr>
<td>Constant</td>
<td>-4.05</td>
<td>-4.29</td>
<td>-4.34</td>
<td>-4.49</td>
</tr>
</tbody>
</table>

| R²           | 99%          | 99%          | 99%          | 99%          |
| Sargan test  | 13.69 (13%)  | 11.90 (22%)  | 11.32 (25%)  | 9.73 (37%)   |
| (P-value)    | 7.27 (61%)   | 7.17 (61%)   | 7.27 (61%)   | 7.17 (61%)   |
### Table 3.5: Marginal Cost Estimates

<table>
<thead>
<tr>
<th>Variable</th>
<th>Collusion</th>
<th>Importers</th>
<th>Plc</th>
<th>Brand</th>
<th>Single Product</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef</td>
<td>t-stat</td>
<td>Coef</td>
<td>t-stat</td>
<td>Coef</td>
</tr>
<tr>
<td><strong>Characteristics:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mpg</td>
<td>-1.6E-3</td>
<td>-0.65</td>
<td></td>
<td></td>
<td>-1.6E-3</td>
</tr>
<tr>
<td>Horsepower</td>
<td>2.5E-3</td>
<td>4.49</td>
<td></td>
<td></td>
<td>2.5E-3</td>
</tr>
<tr>
<td>Length</td>
<td>-2.0E-4</td>
<td>-0.31</td>
<td></td>
<td></td>
<td>2.4E-4</td>
</tr>
<tr>
<td>Height</td>
<td>1.6E-3</td>
<td>0.87</td>
<td></td>
<td></td>
<td>1.6E-3</td>
</tr>
<tr>
<td>cubic capacity</td>
<td>1.6E-4</td>
<td>3.72</td>
<td></td>
<td></td>
<td>1.2E-4</td>
</tr>
<tr>
<td>Acceleration</td>
<td>-0.04</td>
<td>-4.70</td>
<td></td>
<td></td>
<td>-0.04</td>
</tr>
<tr>
<td>Weight</td>
<td>3.7E-4</td>
<td>4.41</td>
<td></td>
<td></td>
<td>3.7E-4</td>
</tr>
<tr>
<td>Automatic gear</td>
<td>0.08</td>
<td>2.13</td>
<td></td>
<td></td>
<td>0.08</td>
</tr>
<tr>
<td>diesel engine</td>
<td>0.15</td>
<td>4.10</td>
<td></td>
<td></td>
<td>0.17</td>
</tr>
<tr>
<td>Firm Dummies</td>
<td>Not Reported</td>
<td>Not Reported</td>
<td>Not Reported</td>
<td>Not Reported</td>
<td>Not Reported</td>
</tr>
<tr>
<td>Seg: 4x4</td>
<td>0.13</td>
<td>1.82</td>
<td></td>
<td></td>
<td>0.17</td>
</tr>
<tr>
<td>Seg: City</td>
<td>-0.07</td>
<td>-1.73</td>
<td></td>
<td></td>
<td>-0.07</td>
</tr>
<tr>
<td>Seg: MPV</td>
<td>0.14</td>
<td>2.41</td>
<td></td>
<td></td>
<td>0.17</td>
</tr>
<tr>
<td>Seg: Exec</td>
<td>0.22</td>
<td>5.30</td>
<td></td>
<td></td>
<td>0.26</td>
</tr>
<tr>
<td>Seg: Medium</td>
<td>0.04</td>
<td>1.09</td>
<td></td>
<td></td>
<td>0.04</td>
</tr>
<tr>
<td>Seg: CV&amp;Coupe</td>
<td>0.38</td>
<td>6.31</td>
<td></td>
<td></td>
<td>0.38</td>
</tr>
<tr>
<td>Constant</td>
<td>8.81</td>
<td>20.73</td>
<td></td>
<td></td>
<td>8.63</td>
</tr>
<tr>
<td>R2</td>
<td>100%</td>
<td>100%</td>
<td></td>
<td></td>
<td>100%</td>
</tr>
<tr>
<td>Sargan test (P-value)</td>
<td>15.3</td>
<td>(93%)</td>
<td>16.3</td>
<td>(90%)</td>
<td>16.5</td>
</tr>
</tbody>
</table>

### 3.5.2 Industry & Firm Profit Analyses

Applying the above estimates into (3-60) we are able to elicit marginal costs and markups for the 837 models. Aggregating over each segment the markups weighted by quantity sold gives us a profit estimate for each segment which we show in Table 3.6. Even though the largest amount of profits are coming from the compact car segment, the expected markups on this market is average. While three times smaller in size, the next most profitable sub-market is the Executive segment. This segment charges some of the largest markups. The two segments experiencing the largest level of concentration, "Executives" and "Convertibles & Coupes" are clearly the segments associated with the largest markups. This pattern confirms the Bain paradigm whereby markets with high level of concentration tend to be most profitable.
### Table 3.6: Profits & Mark Ups across segments

<table>
<thead>
<tr>
<th>Market</th>
<th>Unit Sales</th>
<th>C4 Brands</th>
<th>C4 Importers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>% of Unit</td>
<td>% of Unit</td>
</tr>
<tr>
<td>Segment</td>
<td>Sales by</td>
<td>Within</td>
<td>Within</td>
</tr>
<tr>
<td></td>
<td>Segment</td>
<td>C4 Brands</td>
<td>C4 Importers</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Profits</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(€ Millions)</td>
</tr>
<tr>
<td>Compact (Medium)</td>
<td></td>
<td></td>
<td>Mark Ups</td>
</tr>
<tr>
<td>Cars</td>
<td>31</td>
<td>61</td>
<td>64</td>
</tr>
<tr>
<td>City (Small) Cars</td>
<td>28</td>
<td>48</td>
<td>54</td>
</tr>
<tr>
<td>Medium (Large) Cars</td>
<td>20</td>
<td>58</td>
<td>74</td>
</tr>
<tr>
<td>Executive Cars</td>
<td>10</td>
<td>80</td>
<td>96</td>
</tr>
<tr>
<td>Off Roads, SUV, 4X4</td>
<td>5</td>
<td>55</td>
<td>55</td>
</tr>
<tr>
<td>Multi Purpose Vehicles</td>
<td>5</td>
<td>56</td>
<td>56</td>
</tr>
<tr>
<td>Convertible &amp; Coupe</td>
<td>1</td>
<td>88</td>
<td>93</td>
</tr>
<tr>
<td><strong>Total/Average</strong></td>
<td>100%</td>
<td>(64%)</td>
<td>(70%)</td>
</tr>
</tbody>
</table>

Turning to brand profitability, shown in Table 3.7 and Table 3.8, we note that higher end German brands, **Mercedes**, **BMW**, and **Audi** are the brands expected to extract the largest markups per vehicle. Hyundai however is somewhat unexpected since this brand does appear to implement a quite competitive pricing policy. Likewise finding **Porsche** and **Jaguar** among the producers offering the lowest markups is a surprise. This is due to one of the drawbacks of the nested logit whereby the most expensive cars (usually associated with lower volumes) are connected to lower price elasticities. This pattern is indeed counter intuitive and is addressed chapter 4.

### Table 3.7: Mark Ups across Brands

<table>
<thead>
<tr>
<th>FIRM</th>
<th>Average Price</th>
<th>Expected Markups</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALFA</td>
<td>€25,136</td>
<td>€3,798.8</td>
</tr>
<tr>
<td>AUDI</td>
<td>€37,881</td>
<td>€4,423.0</td>
</tr>
<tr>
<td>BMW</td>
<td>€49,590</td>
<td>€4,821.9</td>
</tr>
<tr>
<td>CHRYSLER</td>
<td>€61,137</td>
<td>€3,750.9</td>
</tr>
<tr>
<td>CITROEN</td>
<td>€21,223</td>
<td>€3,980.3</td>
</tr>
<tr>
<td>KIA</td>
<td>€14,833</td>
<td>€3,820.1</td>
</tr>
<tr>
<td>LANDROV</td>
<td>€64,945</td>
<td>€3,978.6</td>
</tr>
<tr>
<td>LEXUS</td>
<td>€65,359</td>
<td>€3,765.5</td>
</tr>
<tr>
<td>MAZDA</td>
<td>€24,935</td>
<td>€3,947.1</td>
</tr>
<tr>
<td>MERC</td>
<td>€52,082</td>
<td>€5,445.0</td>
</tr>
<tr>
<td>ROVER</td>
<td>€21,709</td>
<td>€3,863.8</td>
</tr>
<tr>
<td>SAAB</td>
<td>€47,483</td>
<td>€3,819.9</td>
</tr>
<tr>
<td>SEAT</td>
<td>€20,790</td>
<td>€4,017.3</td>
</tr>
<tr>
<td>SKODA</td>
<td>€19,246</td>
<td>€4,195.1</td>
</tr>
<tr>
<td>SMART</td>
<td>€21,546</td>
<td>€3,927.7</td>
</tr>
</tbody>
</table>
3.5.3 Investigating Competitive Dynamics & Collusion

To investigate the potential presence of collusion on the Irish market, we test the five following firm behaviours:

**Single Product:**

Pricing behaviours for each firm is aimed at maximizing profits from each single model of car produced in isolation, ignoring existing cross cannibalization between models from the same firm's portfolio. Such a scenario is sub-optimal from a profit maximization point of view since the competitive dynamics reflect the pricing behaviour that is expected from single product firms.

Using formula (3-13), we implement such scenario by setting the ownership matrix $F$ equal to the 827 by 827 identity matrix.\(^{44}\)

**Brand:**

In this setting, firms are conscious that profit gains are to be achieved from incorporating expected consumers' substitution patterns between products falling under the same brand/make. However they do not incorporate the idea that further gains can be achieved if cross substitution patterns are also extended between brands falling under the same ownership.

To implement this setting we just need to set the ownership structure matrix $F$ in (3-13) equal to \(FT.FT\), where $FT$ is an 827 by 35 matrix with each column reflecting the set of dummies related to the following Brands:

---

\(^{44}\) Since in this setting we have 827 "firms" producing only 1 model of car.
Car producers maximize their profits by fully accounting for their ownership structure in terms of make and models.

This time we aggregate further the ownership structure matrix $F$ to reflect the 16 manufacturing corporations:

\[
\begin{array}{cccc}
\text{BMW} & \text{DMC} & \text{Fiat} & \text{Ford} \\
\text{GM} & \text{GM-Daewoo} & \text{Honda} & \text{Hyundai} \\
\text{MG-Rover} & \text{Mitsubishi} & \text{Nissan} & \text{Porsche} \\
\text{PSA} & \text{Renault} & \text{Toyota} & \text{Volkswagen} \\
\end{array}
\]

Once again the ownership structure matrix will be constructed from the following matrix operation:

\[ F = 'Mf.Mf \]

Where $Mf$ is a 827 by 16 matrix with line $j$ and column $i$ set to 1 if model $j$ is manufactured by the $i^{th}$ manufacturing corporation or to zero otherwise.

**Importers:**

Since brands falling under a given importer’s license do not necessarily reflect the PLC ownership structure, we assume that prices reflect a profit maximization behaviour at the importer level rather than the PLC level.

**Collusion:**

This collusion scenario simulates potential collusion between 2 importers: O’Flaherty ($\text{Smart, Mercedes, Mazda, Audi, Skoda, Volkswagen}$) and Armalou ($\text{Seat, Chrysler, Jaguar, Daihatsu, Saab}$).

The pricing behaviour simulates collusion by considering O’Flaherty & Armalou as a single profit maximizing entity, while other competing entities only account for their own portfolio of model produced.

We compute the $F$ matrix in equation (3-13) using the following groups:
Through the Vuong test, shown in Table 3.9, we elicit which of the five associated pricing equations is best supported by the data. The first Table reports the test from the iterative gmm while the second Table is based on the first stage estimation.

As shown in Jaumandreu and Lorences (2002), while the Vuong tests based on the iterative gmm estimation lead to inconclusive results, we are able to get a crisper picture from the first stage gmm. Indeed none of the value in Table 3.9a are significantly different from zero which means that when we update the variance covariance matrix at every round of the search algorithm, the test is unable to discriminate between the models. However when updating the covariance only once, as suggested by Hansen (1982), we conclude that the observed market prices are the output of a Bertrand-Nash equilibrium between the manufacturing corporations rather than importers. Furthermore using the simple specification presented the collusion hypothesis between O’Flaherty and Armalou is not supported by our data.

Table 3.9: Vuong Tests (Iterative)

<table>
<thead>
<tr>
<th></th>
<th>Non Iterative</th>
<th>Collusion</th>
<th>Importers</th>
<th>PLC</th>
<th>Brand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Importers</td>
<td></td>
<td>0.62</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PLC</td>
<td>-0.07</td>
<td>-0.39</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brand</td>
<td>-0.09</td>
<td>-0.4</td>
<td>-0.02</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single Firm</td>
<td>-0.14</td>
<td>-0.16</td>
<td>-0.13</td>
<td>-0.13</td>
<td></td>
</tr>
</tbody>
</table>

45 The shaded area in Table 3.10b clearly shows that the PLC specification leads to a greater fit compared to the other supply side specification. Indeed the Vuong test values on the PLC row are all greater than the critical value of 1.96 (the Vuong test follow a normal standard distribution) which means that the PLC assumption is a better fit than the Collusion or Importers pricing behaviour assumption. While such conclusion can also be reached for the Brand and Single Firm assumption (their respective rows are associated with positive and significant Vuong scores when compared to the Collusion and Importers scenario), both Brand and Single Firm are associated with a significantly lower score when compared to the PLC assumption. Our data therefore supports the superiority of the PLC level pricing compared to the other 3 scenarios.
Table 3.10: Vuong Tests (Iterative)

<table>
<thead>
<tr>
<th>Non Iterative</th>
<th>Collusion</th>
<th>Importers</th>
<th>PLC</th>
<th>Brand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Importers</td>
<td>2.92</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PLC</td>
<td>4.10</td>
<td>33.69</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brand</td>
<td>3.87</td>
<td>29.81</td>
<td>-222.80</td>
<td></td>
</tr>
<tr>
<td>Single Firm</td>
<td>3.09</td>
<td>17.27</td>
<td>-245.53</td>
<td>-287.70</td>
</tr>
</tbody>
</table>

Hence based on the above evidence we will use the PLC model for simulating the impact of the transition VRT regime.

3.5.4 Tax simulation and Incidence

One of the Budget 2008 announcements that generated many headlines was concerned with the reform of the VRT. Partially motivated by environmental issues, the VRT is no longer going to be centered on engine size but rather on CO$_2$ emissions. There are various reasons for considering the VRT system to make it more CO$_2$ emissions related. Under the Kyoto Protocol, Ireland has agreed to limit the growth in greenhouse gas emissions to 13 per cent above 1990 levels in the period 2008-2012. In 1990 CO$_2$ emissions from the road transport sector were under 5 Mt of CO$_2$. Since then CO$_2$ emissions from road transport has more than doubled and is projected to reach over 13 Mt per annum in the period 2008 to 2012.

As expressed by the department of finance, "controlling and reducing CO$_2$ emissions from transport, especially from cars, has an important role to play in reducing the cost to the Exchequer from emissions. It is estimated that in 2005 there were 402 private cars per 1,000 of the population compared to 227 in 1990. On this trend, if no action is taken the total quantity of CO$_2$ emissions relating to car transport will continue to increase.

The new VRT will be gradually introduced through an intermediate phase. One of the suggested options was to adjust engine size tax bands as follow:

Table 3.11: Old Rates vs. Possible New Rates

<table>
<thead>
<tr>
<th>Cars</th>
<th>Old Rate</th>
<th>New Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Up to 1,200ccs</td>
<td>22.5%</td>
<td>15%</td>
</tr>
</tbody>
</table>
### Table 3.11

<table>
<thead>
<tr>
<th>Cars</th>
<th>Old Rate</th>
<th>New Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>1201 to 1400ccs</td>
<td>22.5%</td>
<td>20%</td>
</tr>
<tr>
<td>1401 to 1900ccs</td>
<td>25%</td>
<td>25%</td>
</tr>
<tr>
<td>1901 to 2400ccs</td>
<td>30%</td>
<td>30%</td>
</tr>
<tr>
<td>2401ccs and over</td>
<td>30%</td>
<td>35%</td>
</tr>
</tbody>
</table>

The new rates suggested above would incentivise purchases of smaller cars, with — on average — lower CO₂ emissions.

In the consultation report that preceded the introduction of the reform, the Irish government makes it clear that even though environmental concerns are important, “the VRT is a tax; its principal purpose is to raise revenue for Government services for the population”⁴⁶. Understandably, the government is also concerned with the impact the new VRT regime might have on tax revenue. Such concern is grounded since Vehicle Registration Tax (VRT) is an important source of revenue for the Exchequer, yielding €1.15bn in 2005 and is estimated to yield €1.3bn in 2006. Most of the VRT yield is derived from passenger cars.

In this section, we propose to simulate the expected impact of introducing the aforementioned tax rate.

#### 3.5.4.1 Methodology

We simulate the potential impact by simulating new market prices for each car based on the tax rates from the second column in Table 3.11. Thus, in a short term static scenario, while prices related to cars with an engine size between 1401 and 2400ccs will remain unaffected, larger cars will be 5 per cent more expensive than before and smaller cars will be up to 7.5 per cent cheaper. Such a scenario would assume that the industry does not have time to redesign its pricing policies to incorporate the new changes and its impact on profits.

Through the simultaneous nested logit model estimated previously we have the opportunity to incorporate industry adjustments so as to produce more realistic results based on the new equilibrium prices. The tax change affects both consumers utilities and margins. However in our setting manufacturers react by adjusting their prices. An equilibrium is reached once we find the vector \( P' \) solving the following system of non-linear equations:

⁴⁶ Annex D of “Vehicle Registration Tax, Public Consultation on Options for revising the VRT system to take greater account of CO₂ emission levels”.

- 54 -
\[
\left( \frac{p^n_j}{1 + t_j} - \left( \Omega_{(a, s)}^{-1} \frac{S_{j(P^n_j)}}{1 + t_j} \right) \right) = mc_j
\]

where \( t_j \) is the new tax rate applying to model \( j \).

This system of equations is based on expression (3-10), the key differences being that this time the marginal costs on the right hand side of the above equation are known since we can use the estimates in Table 3.5.

The system however can not be solved analytically since \( P^n \) also appears in the non-linear logit market shares \( S_{j(P^n_j)} \). We therefore use a numerical method to minimize the following objective sum of squares:

\[
\text{Min} \ f(p) = f_1(P^n_1)^2 + \ldots + f_k(P^n_k)^2 + \ldots + f_j(P^n_j)^2
\]

where \( f_k(P^n_k) = \left( \frac{p^n_k}{1 + t_k} - \left( \Omega_{(a, s)}^{-1} \frac{S_{j(P^n_j)}}{1 + t_k} \right) \right) - mc_k \)

Our estimation strategy was implemented through the matlab routine \texttt{lsqnonlin}.

### 3.5.4.2 Simulated Effect of Tax transition

Based on the above methodology we are able to perform some detailed analyses regarding the impact of the tax.

#### 3.5.4.2.1 Impact on Equilibrium Prices:

The Table below provides some insight into the expected price movements. City and compact cars, being equipped with smaller engines, are associated with lower prices compared to the prior period. On the other hands executive cars and especially SUVs are getting more expensive as a result of the tax.

<table>
<thead>
<tr>
<th>Table 3.12: Average equilibrium prices across segments</th>
</tr>
</thead>
<tbody>
<tr>
<td>4x4</td>
</tr>
<tr>
<td>-----</td>
</tr>
<tr>
<td>Average New</td>
</tr>
<tr>
<td>Market Price</td>
</tr>
</tbody>
</table>

\(^{47}\) As these estimates will be unaffected by the tax change.
Since larger cars tend to produce more CO\textsubscript{2} emissions, the predicted market shift towards lower cars might be potentially welcomed by environmentalists. Nonetheless, one should also consider that the increase in the number of cars on the road, due to increased demand, might potentially mitigate the gains.

While demand for 4x4 and executive cars is expected to drop this will be more than offset by the increase in demand for city and compact cars. Given that the total market is also expanding by 4.5 per cent, it is expected that consumers who would not have previously bought a new car\textsuperscript{48} will represent the driving force behind the increase in demand for smaller cars. Given that about 7000 new cars will be added to the road one could question the efficacy of the new policy from an environmental standpoint. This might be less of an issue provided these new cars come to replace second hand cars equipped with potentially less fuel efficient technology.

<table>
<thead>
<tr>
<th>Original Market Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change</td>
</tr>
<tr>
<td>2.4%</td>
</tr>
<tr>
<td>-2.8%</td>
</tr>
<tr>
<td>-0.6%</td>
</tr>
<tr>
<td>2.2%</td>
</tr>
<tr>
<td>1.4%</td>
</tr>
<tr>
<td>-0.6%</td>
</tr>
<tr>
<td>-0.3%</td>
</tr>
</tbody>
</table>

Since larger cars tend to produce more CO\textsubscript{2} emissions, the predicted market shift towards lower cars might be potentially welcomed by environmentalists. Nonetheless, one should also consider that the increase in the number of cars on the road, due to increased demand, might potentially mitigate the gains.

While demand for 4x4 and executive cars is expected to drop this will be more than offset by the increase in demand for city and compact cars. Given that the total market is also expanding by 4.5 per cent, it is expected that consumers who would not have previously bought a new car\textsuperscript{48} will represent the driving force behind the increase in demand for smaller cars. Given that about 7000 new cars will be added to the road one could question the efficacy of the new policy from an environmental standpoint. This might be less of an issue provided these new cars come to replace second hand cars equipped with potentially less fuel efficient technology.

### Table 3.13: Change in quantity and share

<table>
<thead>
<tr>
<th></th>
<th>4x4</th>
<th>City</th>
<th>Compact</th>
<th>Cv Coupe</th>
<th>Exec</th>
<th>Medium</th>
<th>MPV</th>
<th>Total Market</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original Share</td>
<td>4.7%</td>
<td>18.4%</td>
<td>27.3%</td>
<td>1.7%</td>
<td>11.4%</td>
<td>17.4%</td>
<td>3.8%</td>
<td>84.6%</td>
</tr>
<tr>
<td>New Share Share</td>
<td>4.1%</td>
<td>23.8%</td>
<td>28.8%</td>
<td>1.2%</td>
<td>9.1%</td>
<td>18.1%</td>
<td>4.0%</td>
<td>89.1%</td>
</tr>
<tr>
<td>Change</td>
<td>-0.6%</td>
<td>5.4%</td>
<td>1.5%</td>
<td>-0.5%</td>
<td>-2.3%</td>
<td>0.7%</td>
<td>0.3%</td>
<td>4.5%</td>
</tr>
<tr>
<td>Qty Change</td>
<td>-957</td>
<td>8645</td>
<td>2392</td>
<td>-776</td>
<td>-3607</td>
<td>1127</td>
<td>418</td>
<td>7241</td>
</tr>
</tbody>
</table>

**Impact on Government Revenue:**

Such mixed outcomes introduce our next question. Is the government better off as a result of the tax? Based on the equilibrium prices before and after the tax reform we can very easily estimate government revenue by aggregating the tax across cars sold. Note that into the tax \( t \), we incorporate both the VRT and VAT.

\[
Government\ revenue = \sum_{j=1}^{J} (Q_j (P_j^{OMSP} (t^{rat} + t^{vat})))
\]

\textsuperscript{48} Under the market prices before the simulated tax reform.
where $P_{j}^{O MSP}$ is the Open Market Selling Price, $t_{j}^{m}$ is set at 13.4\% and $t_{j}^{m}$ is set using Table 3.11.

Based on our estimation shown in Table 3.14 below, we expect tax revenue to drop by 5 per cent. This decline is mostly driven by the shrinkage of the Executive segment.

Table 3.14: Tax revenue across segments

<table>
<thead>
<tr>
<th></th>
<th>4x4</th>
<th>City</th>
<th>Compact</th>
<th>Cv/Coupe</th>
<th>Exec</th>
<th>Medium</th>
<th>MPV</th>
<th>Total Market</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tax Revenue</td>
<td>€ 109.5</td>
<td>€ 148.4</td>
<td>€ 299.7</td>
<td>€ 47.7</td>
<td>€ 304.2</td>
<td>€ 247</td>
<td>€ 58.1</td>
<td>€ 1,214.6</td>
</tr>
<tr>
<td>(Millions)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>New Tax</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Revenue</td>
<td>€ 88.2</td>
<td>€ 175.6</td>
<td>€ 310.1</td>
<td>€ 31.0</td>
<td>€ 239</td>
<td>€ 255.7</td>
<td>€ 54.2</td>
<td>€ 1,153.8</td>
</tr>
<tr>
<td>(Millions)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Change in Tax</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Millions)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tax Change</td>
<td>-€ 21.4</td>
<td>-€ 27.2</td>
<td>-€ 10.3</td>
<td>-€ 16.8</td>
<td>-€ 65.1</td>
<td>€ 8.8</td>
<td>-€ 3.9</td>
<td>-€ 60.8</td>
</tr>
<tr>
<td></td>
<td>-19.5%</td>
<td>18.3%</td>
<td>3.4%</td>
<td>-35.1%</td>
<td>-21.4%</td>
<td>3.5%</td>
<td>-6.6%</td>
<td>-5.0%</td>
</tr>
</tbody>
</table>

3.5.4.2.2 Impact on Industrial Profits:

Having looked at the overall impact of the tax on equilibrium prices and tax revenue we look at the effect of the proposed reform on the industry profits.

Since marginal cost remains constant before and after the tax reform, we can easily retrieve the markups. Summing up the markups across segments we note that the profits related to City and Compact cars increase substantially by 30 per cent and 12 per cent respectively resulting in nearly 70 million of incremental profits. While this leads to a 2 per cent profit increase across the industry, the remaining segments will be exposed to significant pressure. Convertible, Coupes and Executive cars will be the most seriously affected. We expect manufacturers to be impacted in rather different ways. We therefore look into this in further detail.

Table 3.15: Profits across segments

<table>
<thead>
<tr>
<th></th>
<th>4x4</th>
<th>City</th>
<th>Compact</th>
<th>Cv/Coupe</th>
<th>Exec</th>
<th>Medium</th>
<th>MPV</th>
<th>Total Market</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Profits</td>
<td>€ 37.1</td>
<td>€ 130.4</td>
<td>€ 258.7</td>
<td>€ 27.3</td>
<td>€ 166.6</td>
<td>€ 152</td>
<td>€ 31.9</td>
<td>€ 803.8</td>
</tr>
<tr>
<td>(Millions)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Based on the simulated tax bands one would expect that manufacturers with a strategic focus on large engine cars (e.g. Porsche, Lexus, Landrover or Jaguar) will be most negatively impacted. On the other hand firms specialising in smaller cars (Mini, Smart, Daihatsu, Suzuki or Daewoo) should benefit from the simulated policy. Since we have the new markups available at product level we can easily verify this.

From Table 3.16, we notice that Premium brands like Land Rover, Lexus, Porsche and Jaguar are among the hardest hit brands. This is not a surprise since most of their model portfolio is dedicated to large size engines.

Table 3.16: Profits across brands

<table>
<thead>
<tr>
<th>Make</th>
<th>% Change</th>
<th>Profits before Tax Reform*</th>
<th>Profits after Tax Reform*</th>
<th>Change in Profits*</th>
</tr>
</thead>
<tbody>
<tr>
<td>LANDROVER</td>
<td>-89%</td>
<td>2.17</td>
<td>0.24</td>
<td>-1.93</td>
</tr>
<tr>
<td>SAAB</td>
<td>-86%</td>
<td>2.02</td>
<td>0.28</td>
<td>-1.73</td>
</tr>
<tr>
<td>FIAT</td>
<td>-80%</td>
<td>13.89</td>
<td>2.78</td>
<td>-11.11</td>
</tr>
<tr>
<td>LEXUS</td>
<td>-70%</td>
<td>2.07</td>
<td>0.63</td>
<td>-1.44</td>
</tr>
<tr>
<td>PORSCHE</td>
<td>-55%</td>
<td>0.27</td>
<td>0.12</td>
<td>-0.15</td>
</tr>
<tr>
<td>JAGUAR</td>
<td>-50%</td>
<td>0.75</td>
<td>0.37</td>
<td>-0.38</td>
</tr>
<tr>
<td>CHRYSLER</td>
<td>-41%</td>
<td>0.79</td>
<td>0.47</td>
<td>-0.32</td>
</tr>
<tr>
<td>HONDA</td>
<td>-26%</td>
<td>10.96</td>
<td>8.08</td>
<td>-2.88</td>
</tr>
<tr>
<td>CITROEN</td>
<td>23%</td>
<td>14.16</td>
<td>17.49</td>
<td>3.33</td>
</tr>
<tr>
<td>SEAT</td>
<td>30%</td>
<td>12.19</td>
<td>15.78</td>
<td>3.6</td>
</tr>
<tr>
<td>MG</td>
<td>34%</td>
<td>2</td>
<td>2.67</td>
<td>0.67</td>
</tr>
<tr>
<td>MITS</td>
<td>35%</td>
<td>9.2</td>
<td>12.43</td>
<td>3.22</td>
</tr>
<tr>
<td>KIA</td>
<td>38%</td>
<td>3.45</td>
<td>4.75</td>
<td>1.3</td>
</tr>
<tr>
<td>DAEWOO</td>
<td>43%</td>
<td>8.85</td>
<td>12.7</td>
<td>3.85</td>
</tr>
<tr>
<td>SUZUKI</td>
<td>61%</td>
<td>10.33</td>
<td>16.65</td>
<td>6.31</td>
</tr>
<tr>
<td>SMART</td>
<td>77%</td>
<td>0.12</td>
<td>0.21</td>
<td>0.09</td>
</tr>
<tr>
<td>MINI</td>
<td>85%</td>
<td>3.72</td>
<td>6.89</td>
<td>3.17</td>
</tr>
<tr>
<td>DAIHATSU</td>
<td>119%</td>
<td>1</td>
<td>2.18</td>
<td>1.18</td>
</tr>
<tr>
<td>TOTAL</td>
<td>2%</td>
<td>803.84</td>
<td>823.13</td>
<td>19.29</td>
</tr>
</tbody>
</table>

*All figures expressed in millions
On the other hand, brands like Daihatsu, Smart Suzuki and Daewoo, are heavily positioned on the small size engine segment and do not have any presence in the large engines market and as such benefit from the reforms.

Table 3.17: Most profitable Brands before Tax Reform introduction

<table>
<thead>
<tr>
<th>% Change</th>
<th>Profits before Tax Reform (millions)</th>
<th>Profits after Tax Reform (millions)</th>
<th>Change in Profits (millions)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TOYOTA</td>
<td>-1%</td>
<td>€111.31</td>
<td>€110.07</td>
</tr>
<tr>
<td>MERCEDES</td>
<td>-15%</td>
<td>€106.40</td>
<td>€90.74</td>
</tr>
<tr>
<td>NISSAN</td>
<td>40%</td>
<td>€91.28</td>
<td>€128.16</td>
</tr>
<tr>
<td>FORD</td>
<td>19%</td>
<td>€60.00</td>
<td>€71.43</td>
</tr>
<tr>
<td>TOTAL</td>
<td>2%</td>
<td>€803.84</td>
<td>€823.13</td>
</tr>
</tbody>
</table>

In Table 3.17 and Table 3.18, we only focus on the largest producer we observe mixed results. While Toyota will be able to maintain its leading position, German brands like Mercedes, BMW and especially Volkswagen are severely exposed.

Table 3.18: Most profitable Brands after Tax Reform introduction

<table>
<thead>
<tr>
<th>% Change</th>
<th>Profits before Tax Reform (millions)</th>
<th>Profits after Tax Regime (millions)</th>
<th>Change in Profits (millions)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RENAULT</td>
<td>13%</td>
<td>€53.87</td>
<td>€60.79</td>
</tr>
<tr>
<td>OPEL</td>
<td>0%</td>
<td>€48.00</td>
<td>€48.06</td>
</tr>
<tr>
<td>VW</td>
<td>-57%</td>
<td>€46.45</td>
<td>€20.19</td>
</tr>
<tr>
<td>BMW</td>
<td>-23%</td>
<td>€40.38</td>
<td>€31.00</td>
</tr>
<tr>
<td>TOTAL</td>
<td>2%</td>
<td>€803.84</td>
<td>€823.13</td>
</tr>
</tbody>
</table>

3.5.4.2.3 Impact on Consumers:

Having looked at the government and the industry we now focus on consumers.

With the post-Tax reform prices in hand, we can estimate expected consumer welfare changes due to the tax policy under consideration. A consumer’s expected change in utility due to the tax may be evaluated as the change in her logit inclusive value (McFadden [1981], Small and Rosen [1981]). Therefore, the compensating variation for individual i is the change in her logit inclusive value
divided by the marginal utility of income\textsuperscript{49}. When prices enter the utility function linearly, which holds in our case, the compensating variation is given by:

\[ CV_i = \frac{\ln \left( \sum_{j=0}^{J} \exp(V^{\text{post}}_{ij}) \right) - \ln \left( \sum_{j=0}^{J} \exp(V^{\text{pre}}_{ij}) \right)}{\alpha_i} \]  

where \( V^{\text{pre}}_{ij} \) and \( V^{\text{post}}_{ij} \) are the mean utilities using the pre- and post-tax reform prices. Integrating over the density of consumers yields the average change in consumer welfare from the tax change. The consumer surplus are calculated as follows\textsuperscript{50}:

\[ W = \frac{\log(\sum_{\sigma} D_i^{\sigma})}{\alpha} \]

Although we expected the smaller car segments (city and compacts) to benefit from the transition regime, the 25 per cent welfare gain for city car buyers is clearly substantial. The large engine sizes traditionally found on executive cars, convertibles and off road vehicles explain most of the drop in consumer surplus observed in Table 3.19.

<table>
<thead>
<tr>
<th>Table 3.19: Profits across segments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
</tr>
<tr>
<td>Market</td>
</tr>
<tr>
<td>CS</td>
</tr>
<tr>
<td>Post Reform CS</td>
</tr>
<tr>
<td>Prior Reform Change in CS</td>
</tr>
<tr>
<td>Per Consumer</td>
</tr>
</tbody>
</table>

\textbf{3.6 Conclusion & Policy Implications}

Through the use of a structural model, we have discussed how game theory and, more precisely, the Bertrand-Nash equilibrium, can be leveraged to back out marginal costs consistent with such equilibrium. This step represents the fulcrum of our analysis since, not only are we able to infer firms’ profit levels, we can also test whether the observed equilibrium prices and quantities are consistent with collusive behaviour between various sets of manufacturers and importers. Based on the Vuong Test we saw that our unique dataset is not supportive of a collusive behaviour between

\textsuperscript{49} Which is simply \( \alpha \) since we assume a utility specification linear in income.

\textsuperscript{50} See Fershtman & Al(1999) and McFadden (1978) for details.
importers. Instead the data provide some evidence that manufacturers maximize profits across their respective portfolio. Thus from a pricing strategy viewpoint, manufacturers in this industry are quite sophisticated compared to our initial presumptions.

Without the presence of collusion, we conclude that prices prevailing on the Irish market stems from a combination of factors involving both a large level of tax and the affluence experienced by most Irish consumers. Indeed while it is known that automotive related taxes in Ireland are amongst the highest in Europe, the Irish automotive industry has nonetheless been doing rather well, with importers consistently being ranked amongst the most profitable businesses. Ultimately, one is tempted to point out the solid economic growth from the last decade as one of the main drivers behind the strong demand for new cars in the country.

While the findings and methodology in this paper will be of interest to many competition authorities, policy makers should also find our empirics valuable. By modelling demand and supply simultaneously, we were able to use the model to simulate the new equilibrium triggered by the change in VRT tax. Based on the Nested specification the simulated tax reform would generate a loss in government revenue of about €61 million, but it would increase industry profits by 19 millions and create an average Consumer Surplus of €1,758 per consumer. For the total market this represents a potential social gain of 234 millions.\(^{51}\)

Given this setting it seems that from a welfare point of view, VRT reforms will benefit consumers most. The large gain in Consumer Surplus on the entry level segment is congruent with the 5 per cent market expansion.\(^{52}\)

Yet over the short term, the tax reform could be seen as a failure for the government officials who were expecting to protect their tax stream. Their decisions might have underestimated the substitution effects occurring at consumer levels. It is worth mentioning that the long term picture could be quite different, especially since newer cars tend to be both safer and cleaner to run, both the Health board and the environment should benefit, the latter point being quite timely given on-going concerns regarding oil resources. As governments across the world implement similar policies, manufacturers are expected to respond over time by focusing their R&D efforts on combustion efficiencies. Our analyses indirectly support such a scenario since Brands specializing in smaller cars end up better off as a result of the tax reform.

Finally one might wonder whether the elasticities traditionally associated with the nested logit (whereby more expensive cars tend to be associated to higher price elasticities) is not driving this outcome. Consequently there are clear benefits in applying the present framework to a BLP

\(^{51}\) \(€1,758 \times 133,000 = €234m\).

\(^{52}\) The share of the outside option drops from 15.4\% to 10.8\%. 

- 61 -
simulation which, despite being more complicated to implement, has been shown to drive more realistic substitution patterns. This is the scope of chapter 4.
APPENDIX 3.1

Markups under a Cournot-Nash Equilibrium

Starting from the profit function in 3-1,

\[ \Pi_j = \left( \frac{p_1}{1+t} Q_1 - Q_1 C_1 \right) + \left( \frac{p_2}{1+t} Q_2 - Q_2 C_2 \right) + \ldots + \left( \frac{p_n}{1+t} Q_n - Q_n C_n \right) - FC_j \] 3-67

The associated FOCs under a Cournot game with fixed marginal costs are

\[ \frac{\partial P_1}{\partial Q_1} + \ldots + \frac{\partial P_k}{\partial Q_k} + \ldots + \frac{\partial P_n}{\partial Q_n} = \left( \frac{P_1}{1+t} - C_1 \right) \] 3-68

As in 3-3, we replace the markups respectively and rewrite the FOCs in matrix form as:

\[ \begin{bmatrix} \frac{\partial P_1}{\partial Q_1} & \ldots & \frac{\partial P_k}{\partial Q_k} & \ldots & \frac{\partial P_n}{\partial Q_n} \\ \frac{\partial P_1}{\partial Q_1} & \ldots & \frac{\partial P_k}{\partial Q_k} & \ldots & \frac{\partial P_n}{\partial Q_n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \frac{\partial P_1}{\partial Q_1} & \ldots & \frac{\partial P_k}{\partial Q_k} & \ldots & \frac{\partial P_n}{\partial Q_n} \end{bmatrix} \begin{bmatrix} Q_1 \\ Q_1 \frac{1+t}{1+t} \\ \vdots \\ Q_k \frac{1+t}{1+t} \\ \vdots \\ Q_n \frac{1+t}{1+t} \end{bmatrix} = \begin{bmatrix} x_j \\ \vdots \\ x_k \\ \vdots \\ x_n \end{bmatrix} \] 3-69

We note that unlike under a Bertrand equilibrium, the Cournot markups do not require any matrix inversion and are therefore likely to be easier to compute providing we can define an inverse demand function expressing price as a function of quantities.
Elasticities and Derivatives

Derivation of $\frac{\partial s_r}{\partial P_j}$

Since

$$\frac{\partial s_r}{\partial P_j} = \frac{\partial s_r}{\partial \delta_j} \cdot \frac{\partial \delta_j}{\partial P_j} = \frac{\partial s_r}{\partial \delta_j} \cdot \frac{\partial s_r}{\partial P_j}$$

We will only focus on $\frac{\partial s_r}{\partial \delta_j}$

$$S_r = \frac{e^{\delta_r/(1-\sigma)}}{D_g^\sigma \left( \sum_g D_g^{1-\sigma} \right)}$$

$$D_g = \sum_{r \in G_g} e^{\delta_r/(1-\sigma)}$$

$$\frac{\partial S_r}{\partial \delta_j} = \frac{\partial}{\partial \delta_j} \left[ \frac{e^{\delta_r/(1-\sigma)}}{D_g^\sigma \left( \sum_g D_g^{1-\sigma} \right)} \right]$$

$$= \frac{\partial}{\partial \delta_j} \left[ \frac{\frac{\partial}{\partial \delta_j} \left( \sum_g D_g^{1-\sigma} \right)}{D_g^\sigma} \right]$$

Substituting:

$$\frac{\partial e^{\delta_r/(1-\sigma)}}{\partial \delta_j} = \frac{e^{\delta_r/(1-\sigma)} \cdot \sigma D_g^{\sigma-1} e^{\delta_r/(1-\sigma)} \sum_g D_g^{1-\sigma} + e^{\delta_r/(1-\sigma)}}{D_g^\sigma \left( \sum_g D_g^{1-\sigma} \right) D_g^\sigma \left( \sum_g D_g^{1-\sigma} \right)}$$

Case 1: $j \neq r \land j \notin g$

$$\frac{\partial s_r}{\partial \delta_j} = \frac{-e^{\delta_j/(1-\sigma)} | e^{\delta_r/(1-\sigma)} |}{D_g^\sigma \left( \sum_g D_g^{1-\sigma} \right) D_g^\sigma \left( \sum_g D_g^{1-\sigma} \right)} = -S_r S_j$$

Case 2: $j \neq r \land (j,r) \in g$

$$\Omega = \begin{pmatrix} \frac{\partial s_1}{\partial P_1} & \ldots & \frac{\partial s_1}{\partial P_j} \\ \frac{\partial s_2}{\partial P_1} & \ldots & \frac{\partial s_2}{\partial P_j} \\ \vdots & \ddots & \vdots \\ \frac{\partial s_n}{\partial P_1} & \ldots & \frac{\partial s_n}{\partial P_j} \end{pmatrix}$$
\[ \frac{\partial S_r}{\partial \delta_j} = -e^{\delta_j, (l-1)} \left[ \frac{\sigma}{1-\sigma} D_{r\&jeg}^{\sigma-1} e^{\delta_j, (l-1)} (\sum_g D_g^{l-1}) + e^{\delta_j, (l-1)} \right] \]
\[ = -S_r \left( \frac{\sigma}{1-\sigma} S_{r/g} + S_j \right) \]

Case 3: \( j=r \)

\[ \frac{\partial S_r}{\partial \delta_j} = -e^{\delta_j, (l-1)} \left[ \frac{\sigma}{1-\sigma} D_{r\&jeg}^{\sigma-1} e^{\delta_j, (l-1)} (\sum_g D_g^{l-1}) + e^{\delta_j, (l-1)} \right] \]
\[ = -S_r \left( \frac{\sigma}{1-\sigma} S_{r/g} + S_j \right) \]
4

THE INFLUENCE OF DIFFERENT METHODOLOGIES
ON HETEROGENEOUS DEMAND ESTIMATION WITH
DIFFERENTIATED GOODS

4.1 Introduction

In this chapter, our goals are fourfold. First, we address some of the shortcomings associated with the logit specification seen in the previous chapter. For instance, while such models are reasonably easy to implement, the elasticities tend to be higher for more expensive products while cheaper alternatives are associated with lower own price elasticities. Nonetheless such a pattern is counterintuitive since more expensive brands tend to be purchased by more wealthy individuals for whom money is usually less of an issue. We therefore would expect the opposite pattern, whereby cheaper products are associated with larger own price elasticities. The logit elasticity formula substantiates our explanation:

\[ e_{ij} = \alpha p_j \left( 1 - s_j \right) \]

Based on the above formula and assuming \( \alpha < 0 \), we note that when \( s_j \) is small enough, the own price elasticity will be close to \( \alpha p_j \). This implies that when the price of \( j \), \( p_j \), is high, demand is less elastic. Another limitation already seen in the previous chapter relates to the IIA property which we illustrate through the famous blue bus / red bus example from McFadden.

When commuters decide between going to work by either taking a red bus, a blue bus or their own car, car users are expected to be less affected by a fare increase applied to the blue bus. However the cross price elasticity of the nested logit leads to a different conclusion:

---

53 We use the result in Appendix 3.2 and set \( \sigma = 0 \) to obtain formula 4-1.
54 This scenario clearly applies to our dataset since the average market share is 0.001% and the largest share is 2.59%.
55 Independence of Irrelevant Alternative – See previous chapter for further details.
\[ e_{\text{car,bluebus}} = \frac{\partial s_{\text{car}}}{\partial p_{\text{bluebus}}} \cdot p_{\text{bluebus}} \cdot s_{\text{car}} = \alpha p_{\text{bluebus}} s_{\text{bluebus}} \]

\[ e_{\text{redbus,bluebus}} = \frac{\partial s_{\text{redbus}}}{\partial p_{\text{bluebus}}} \cdot p_{\text{bluebus}} \cdot s_{\text{redbus}} = \alpha p_{\text{bluebus}} s_{\text{bluebus}} \]

Under the logit utility specification, a fare increase applied to the blue bus will impact equally the share of red bus commuters and car commuters. Yet, the share of red bus commuters is expected to be more impacted than the share of people commuting by car. Nonetheless we have seen in the previous chapter that the nested logit addresses the IIA property across each nest, nonetheless the IIA feature will prevail within each nest, regardless of product similarities. Fortunately, we will see that, despite its difficulty of implementation, the random coefficient model is a good alternative to the logit specification. Its flexible form takes into account product similarities by allowing consumers with similar taste to pick similar products as substitute. Another critique specific to the nested logit is that the nests have to be constructed using prior information as opposed to being defined through the data. Thus the researcher will need to defend the nesting structure since results can be affected when a different structure is chosen.

Our second objective is to compare two different methods to estimate the same random coefficient model, namely GMM estimation and Bayesian estimation. Following the latest progress in the field of Bayesian econometrics applied to demand estimation, we contrast the potential benefits of such estimation framework against the GMM estimation methodology. This chapter will assess to what extent the output differs across methods and whether the associated substitution patterns are in line with intuition. A contribution of this chapter is the extension of the Bayesian estimation from Jiang, Machanda and Rossi (2007)\(^{56}\). We extend their work by incorporating the effect of demographic variables through empirical distributions extracted from the Quarterly Household Survey issued by the CSO in 2003.\(^{57}\)

Our overall goal is to better understand substitution patterns of Irish consumers when purchasing a new car. In doing so we explore the ability of the methodologies to generate credible outputs.

In the next section we present the Random coefficient models and highlight key differences with the Nested logit. We discuss the two methodologies used to estimate this model in section 3. In the fourth section we show how the Bayesian estimation can be extended to account for demographic distributions. The principal conclusions and future research make up the final section. Throughout the chapter we complement the usual demand estimation based on physical product characteristics by incorporating perceived benefits through the use of industry experts’ reviews. By focusing more on

\(^{56}\) Henceforth JMR (2007).

\(^{57}\) In this chapter we will use the age of chief income earner in the household whether at least one child is present in the household.
the benefits delivered by the physical characteristics rather than the characteristics per se, we build a specification which better reflects consumers’ decision processes when choosing a new car.\footnote{For instance, instead of using \textit{Horsepower} as in Berry, Levinsohn and Pakes (1995) we will be using \textit{Performance} which is part of the benefit extracted from owning a car with large amount of horsepower.}

### 4.2 Addressing the Nested Logit Limitations with the Random Coefficients Logit\footnote{Henceforth RCL.}

The nested logit utility specification we estimated in the last chapter takes following form:

\[
U_{ij} = \delta_{ij} + \zeta_{ig} + (1-\sigma)\epsilon_{ij}
\]

The mean utility for product \( j \), \( \delta_{ij} \), across all consumers \( i \) is expressed as \( \delta_{ij} = X_{ij}\beta + \alpha p_{ij} + \xi_{ij} \) where \( X_{ij} \) is a vector of characteristics for product \( j \), \( p_{ij} \) is its price and \( \xi_{ij} \) capture the utility associated with characteristics unobserved by the econometrician.\footnote{Similar to the previous chapter, we assume that both consumers and suppliers are knowledgable about the amount of quality unobserved to the econometrician. Thus endogeneity of prices not only exits due to the simultaneity of demand and supply but will also be manifest through an omitted variable problem.}

Consumer heterogeneity is entering through \( \zeta_{ig} + (1-\sigma)\epsilon_{ij} \) where \( \zeta_{ig} \) is the marginal utility associated with group \( g \) regardless of other characteristics, \( \epsilon_{ij} \) is individual \( i \) taste for product \( j \) and \( (1-\sigma) \) accounts for the correlation between the unobserved components of utility for alternatives within a nest \( g \), thereby making \( (1-\sigma)\epsilon_{ij} \) totally idiosyncratic.\footnote{Daly & Zachary (1978), McFadden (1978), Williams (1977).} The larger \( \sigma \), the more correlated will be the preferences for products belonging to the same nest \( g \).

While the nested logit diminishes the IIA issue mentioned in the previous section, the fix is only partial since products located in the same nest will still be affected by the IIA property. For instance, consider the market for cars and assume one of the nests is composed by the 4x4 segment. If the price of a 4x4 model with a very large engine increases, the consumer is as likely to substitute towards another SUV with small engine as s/he is to substitute towards a SUV with engine of similar size. While this issue can potentially be addressed by including an extra nest (engine size), the cross substitution patterns are imposed a priori (as opposed to being estimated and the findings will rely on the nesting assumptions). When we consider the importance of these substitution patterns for antitrust economists and marketing professionals alike, the aforementioned limitations can not be ignored.

\[ -68 - \]
To deal with these limitations using our car dataset, we need a model offering more flexibility which can be estimated from aggregate data.

To do so Berry, Levinsohn and Pakes (1995) estimate the utility of consumer $i$ for product $j$ through the following Random Coefficients Logit model:

$$U_i = X_i \beta_i + \alpha_i p_i + \xi_i + \varepsilon_{ij}$$

Where observed characteristics $X_i$ vary with the product being considered while the marginal utility conveyed by a given characteristic varies across consumers. We apply the model to our car industry data set described in chapter 1. The characteristics included are vehicle consumption (Miles per gallon), Weight (as a proxy for safety and comfort), Performance, Running Cost, Value for Money and obviously Price. We also capture brand specific unobserved quality by including brand dummies while unobserved segment specific features are represented by the appropriate dummies. This gives the following unobserved quality index:

$$\tilde{\xi}_j = f_j + G_j + D_j$$

where $f_j$ is a set of Brand specific dummies and $G_j$ is a set of row vectors indicating the segment in which product $j$ belongs (City, 4x4, MPV, Medium, Coupe or Compact).

Thus, in this model, tastes for product characteristics and price vary across consumers. Such heterogeneity is achieved by specifying individual preferences through the following random coefficients:

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi D_i + \Sigma v_i$$

$\alpha$ is the mean valuation of price across all consumers and is expected to be negative, $\beta$ represent the mean market valuation of the observed non price characteristics of the cars. Heterogeneity across consumers is accomplished through the presence of $D_i$ and $v_i$. $D_i$ is the matrix of observed demographics and $v_i$ captures consumer $i$'s deviation from the mean valuation of unobserved characteristics which matters to the purchase decision. $\Pi$ and $\Sigma$ are vectors of parameters we want to estimate.

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63 See Chapter 1 for further details.
64 $v_i$ is iid and follow a standard normal distribution by assumption and as such can take positive or negative values. On the other hand the diagonal components of $\Sigma$ are all positive and reflect the amount of taste heterogeneity for each characteristic. This heterogeneity stems out from unobservable individual characteristics (such as ‘owning a dog’).
Following BLP (1995) we express (4-6) by making a distinction between the mean utility of each product and consumers’ specific parameters:

\[
U_y = X_j \beta + \alpha_j p_j + \xi_j + \sum_{k=1}^{K} \left( \sigma_{ik} \nu_i^k + \pi_{ik} D_{ik} + \cdots + \pi_{id} D_{id} \right) + \varepsilon_y \tag{4-7}
\]

Following Nevo (2000), the indirect utility in (4-7) can be decomposed in two parts: a mean utility given by \( \delta_j = X_j \beta + \alpha_j p_j + \xi_j \) and a deviation from that mean, which is a function of the interaction between the consumer’s characteristics and the brand features. \(^{65}\) This individual specific part is given by:

\[
\nu_y = \sum_{k=1}^{K} \left( \sigma_{ik} \nu_i^k + \pi_{ik} D_{ik} + \cdots + \pi_{id} D_{id} \right) \tag{4-8}
\]

To complete the model we specify an outside option. Consumer \( j \) can decide not to purchase any of the \( J \) products when the outside good receives a higher utility score:

\[
U_{y0} = \sigma_{00} D_i + \nu_{00} + \varepsilon_{yo} \tag{4-9}
\]

The utility of the outside good is normalized to equal zero. This is of no consequence since choices based on utility are “level invariant”\(^{66}\).

Given the observed and unobserved consumer characteristics, the choice set is defined by

\[
S(X_j, p_j, \xi_j; \theta) = \{D_i, \nu_i, \varepsilon_y\} : U_{yi} > U_{y0} \forall k = 0,1,\ldots,N \tag{4-10}
\]

where \( \theta \) is a vector which includes all the parameters of the model.

Each household purchases one unit of the brand yielding the highest utility. The global market share of the \( j^{th} \) brand corresponds to the probability the \( j^{th} \) brand is chosen. When assuming that \( D, \nu, \) and \( \varepsilon \) are independents, this probability is given by

\[
s_j = \int I\{D_i, \nu_i, \varepsilon_y\} : U_y \geq U_{y0} \forall k = 0,1,\ldots,N \} dH(D) dG(\nu) dF(\varepsilon) \tag{4-11}
\]

Where \( I \) is an indicator function. Depending on the assumptions regarding \( D, \nu, \) and \( \varepsilon \), this integral can have an analytic solution. However when dealing with a more general setting, this integral does not have an analytic solution and should be solved numerically (BLP(1995); Nevo(2000), Villas-Boas (2002)).

\(^{65}\) Observed and unobserved Individual characteristics as expressed respectively through \( v_i \) and \( D_i \).

\(^{66}\) If we increase a individual’s utility by a given constant across all the utilities she has assigned to each product. Her choice remains unaffected since the product with the highest utility remains the same.
To estimate (4-11) we follow Nevo (2000) by using the smooth estimator in (4-12) and we assume an extreme value distribution on $\varepsilon_y$ to net them out analytically. The predicted market shares are approximated by

\[ s_j(p, x, \delta, P_m; \theta_2) = \frac{1}{nS} \sum_{r=1}^{nS} \frac{\exp(\delta_j + \mu_j)}{1 + \sum_{m=1}^{nS} \exp(\delta_m + \mu_m)} \]

Where $ns$ is the number of draws from the distribution $D$ and $v$ given by the distribution $P_m$.

### 4.3 Estimation

In this section we expose the details behind the two estimation methods deployed in the empirical part. The first method used is the simulation process introduced by BLP which uses the general method of moments (GMM). While we also use GMM to estimate the nested model in the previous chapter, it was implemented in a simultaneous setting. This time we focus on the demand side. Though one can argue that a simultaneous setting is more efficient, a simpler non simultaneous setting may also be more robust since any misspecification will be contained to only one equation as opposed to spread across the whole system through the variance covariance. For the second method we turned to a Bayesian estimation framework.

#### 4.3.1 The BLP Approach through GMM

As expressed through equation (4-7), the impact of unobserved product characteristics is captured by $\zeta_j = \delta_j - X\beta_j - \alpha_j \epsilon_j$. $\zeta_j$ is in fact the econometric error we interact with the instruments to build the required orthogonal conditions. Due to simultaneity and omitted variable bias, prices are expected to be correlated with the error terms. Thus, we must choose an estimation technique that will account for this endogeneity. In such context the General Method of Moments is a natural choice.

The overall intuition behind the estimation strategy initially laid out by Berry (1994) is well conveyed through Nevo (2000) which we mostly follow in our exposition.

The goal is to construct a GMM function whereby given a value of the unknown parameters, the error terms are computed and interacted with exogenous instruments to form the objective function. An iterative process selects the estimators minimizing this objective function.

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67 See comments from Verboven who used a sequential setting in his study of the EU car market.

68 We refer the reader to the previous chapter for a full exposition of the covariance matrix.

69 Berry (1994).

70 Nevo (2000).
Let us define the vector of instruments $Z = [z_1, \ldots, z_m]$ such that

$$E[Z m^{(\theta^*)}] = 0, \quad m = 1, \ldots, M$$

Where $\theta^*$ denotes the vector of 'true' parameters. The GMM estimate of (4-7) is

$$\hat{\theta} = \arg \min_{\theta} \xi(\theta)'Z\Phi^{-1}Z'\xi(\theta)$$

Where $\Phi^{-1}$ is a consistent estimate of $E[Z'\xi'Z]$ estimated through 2 stages. The matrix $\Phi^{-1}$ will give a lower weight to the less 'precisely defined' moments, i.e. those with a higher variance. Since we are using more than one independent instrument we cannot set simultaneously all the moment conditions to zero. Instead we minimize the objective function in (4-14).

While the process is relatively straightforward to implement when dealing with linear parameters such as $(\alpha, \beta)$, we must also estimate $\Pi$, the non-linear parameters. To do so we follow the steps suggested by BLP. First we need to sample consumers to construct the matrix of individuals' characteristics $D$ and the vector of individuals' unobserved characteristics $v$. We select a set of starting values for the non-linear parameters. Conditional on these starting values, we can then use the contraction map suggested by Berry to get the mean utilities $\delta_j$ minimizing the difference between actual and calculated shares. Since $\delta_j$ is a linear function of the mean parameters $(\alpha, \beta)$ we can use a closed form IV estimation to retrieve them.

Given our vector of parameters $(\alpha, \beta, \Pi)$, we compute the vector of unobserved characteristics, $\xi(\theta)$, which is interacted with the exogenous instruments $Z$.

We reiterate the above steps using a grid search procedure until the objective function converges to a minimum. We now detail the required steps:

To draw individuals we use the Household Budget Survey conducted in 2000 and made available by the CSO through an anonymised dataset. This survey is carried out every 5 years by the Central Statistics Office to measure the expenditure and income of households. It covers a representative random sample of all private households in the country. A detailed record of household expenditure is recorded by members of the household over a 2 weeks period. The data from the Household Budget Survey is used as the basis for the weighting of items in the CPI. Detailed demographics data is also collected on each household member and its chief income earner. 7,644 households participated in the 1999-2000 HBS.

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71 In the 1st stage we set this weighting matrix to $Z'Z$ to get a consistent estimate of $\xi$ under the assumption of homoscedastic errors.

72 Using equation (4-6).
Using this dataset we are able to construct a $D$ matrix used in (4-6) and containing demographic information on Gender, Age of the head of the household as well as presence of a child in the household. This dataset provides a useful empirical distribution of observed consumer characteristics. The unobserved characteristics of individuals, $v$, are assumed to be normally distributed and are simulated accordingly.

For each interacted demographic variables we associate a randomly chosen set of non-linear parameters $(\sigma, \pi)$. Using these parameters we can calculate (4-7) for each product and each individuals. At this stage we are in a position to express the probability of purchases in (4-11) and we apply Berry’s contraction map to retrieve the mean product utilities, $\delta$:

$$\delta_{\text{new}} = \delta_{\text{old}} + \ln(S) - \ln(s(p, x, \delta_{\text{old}}, \mathcal{P}_{\pi};(\sigma, \pi)))$$

4-15

Berry shows that the above converges to a unique solution where the calculated market shares equal the observed ones.

Once the inversion has been computed the error term is defined as:

$$\xi_j = \delta_j((\sigma, \pi) - \beta + \delta\alpha_p)$$

4-16

This error is interacted with the instrumental variables, $Z$, to form the objective GMM function:

$$\xi(\alpha, \beta, \sigma, \pi) = Z\Omega^{-1}Z' \xi(\alpha, \beta, \sigma, \pi)$$

4-17

The computing burden can be lessened since we can get the linear parameters $\alpha$ and $\beta$ analytically through the FOC:

$$\begin{bmatrix} \alpha \\ \beta \end{bmatrix} = (X'Z\Omega^{-1}Z'X)^{-1}X'Z\Omega^{-1}Z'\delta(\sigma, \pi)$$

4-18

In other words we reduce computing time by limiting the non-linear search to $\sigma$ and $\pi$. Since the Nelder Mead algorithm has proven reliable with non-linear objective functions this is the search algorithm we implement in Matlab.

4.3.2 The Bayesian Estimation

As a result of relatively recent breakthroughs in MCMC computation (along with a consistent increase in computing power), Bayesian econometrics are being used more often by the research community.

According to Train (2003), the Bayesian procedures avoid two of the most prominent difficulties associated with classical procedures. First, Bayesian estimations do not require maximization of any function which can be an advantage especially when the GMM/Nelder Mead algorithm fails to
converge.\textsuperscript{73} Furthermore the choice of starting values is often critical to avoid convergence to local as opposed to global minima. To some extent, such a situation is less a concern when using Bayesian methods. Indeed the Bayesian procedure does not attempt to look for a maxima. Chib and Greenberg (1995) explain why one of the most powerful algorithm used by Bayesians (i.e. the Metropolis Hasting algorithm) works regardless of the complex of the distribution we try to draw from, while Lancaster (2004) provides the condition securing the convergence of the algorithm regardless of the initial state through theorems 4.4 and 4.5. Namely the chain needs to be aperiodic, irreducible and ergodic.\textsuperscript{74}

Second, desirable estimation properties, such as consistency and efficiency, can be attained under more relaxed conditions with Bayesian procedures than classical ones.

Despite its practical benefits Bayesian estimation also presents its own difficulties. A limitation specific to the estimation of BLP model is that it requires an explicit assumption on the distribution of the aggregate shock $\xi_j$ spelled out in equation 4-38. Two other downsides are more generic. First, the "Philosophy" behind Bayesian estimation is very different from classical econometrics. While the later relies on concepts articulated around the mathematics of optimization (i.e. finding a maximum or a minimum of a given objective function), Bayesian estimation is articulated around a recursive application of Bayes theorem. For some of us this change of perspective can be unsettling. Secondly, learning about the relevant algorithms (i.e. Markov Chain Monte Carlo methods such Gibbs sampling or the Metropolis Hasting algorithm) is not straightforward.

Although the learning curve can be steep, the returns associated with Bayesian econometrics deserve some attention. In the next section we present some Bayesian concepts and convey the intuition behind the methodology through a simple example.

### 4.3.2.1 Concepts behind the Bayesian Estimation\textsuperscript{75}

Consider a model with parameter $\theta$ and assume we have some initial ideas about the value of these parameters. Let us represent our initial belief about the parameters by a probability distribution over all possible values these parameters can take. This probability represents how likely we think it is for $\theta$ to take particular values. Our beliefs can be based on logic, intuition, or past analyses. These ideas are represented through a density on $\theta$, which we call the prior distribution $p(\theta)$.

To check our beliefs, suppose we observe a sample of $N$ consumers. $y_{it}$ denotes the observed choice of consumer $N$ and let's label the entire set of observed choices as $Y = \{y_{i1}, \ldots, y_{in}\}$. Based on the outcome,
we then update our beliefs about $\theta$. The updated beliefs are represented by a new density on $\theta$, $p(\theta|Y)$, the posterior distribution. This posterior distribution depends on the data, $Y$, since it incorporates the information contained in the observed sample.

Bayes rule establishes the relation between the posterior, $p(\theta|Y)$, and the prior, $p(\theta)$.

Let $p(y_n|\theta)$ be the probability of outcome $y_n$ for decision maker $n$. This probability is the behavioural model relating the explanatory variables and the parameters to the outcome. The probability of observing the sample outcome $Y$ is given through the following likelihood depending on $\theta$

$$L(Y | \theta) = \prod_{n=1}^{N} p(y_n | \theta).$$  \hspace{1cm} 4-19

Bayes' rule provides the mechanism by which we improve our ideas about $\theta$. By the rule of conditioning,

$$p(\theta|Y)L(Y)=L(Y|\theta)p(\theta)$$  \hspace{1cm} 4-20

where $L(Y)$ is the marginal probability of $Y$ over $\theta$

$$L(Y) = \int L(Y | \theta)p(\theta)d\theta$$  \hspace{1cm} 4-21

We can therefore express $p(\theta|Y)$ as

$$p(\theta|Y) = \frac{[L(Y|\theta)p(\theta)]}{L(Y)}$$  \hspace{1cm} 4-22

This equation is Bayes' rule applied to prior and posterior distributions. As explained by Train (2003), Bayes' rule links conditional and unconditional probability and does not imply a Bayesian perspective on statistics. Bayesian econometrics occurs when the unconditional probability is the prior distribution $p(\theta)$ based on some initial beliefs regarding the probable distribution of the parameters while the conditional probability, $p(\theta|Y)$ is the posterior distribution which has been updated based on the data at hand.

The marginal density of $Y$, $L(Y)$, is constant with respect to $\theta$ and is the numerator of the previous expression. Hence $L(Y)$ is simply the normalizing constant ensuring that the posterior distribution, $p(\theta|Y)$, integrates to 1. The previous expression is then proportional to the prior distribution $p(\theta)$ times the likelihood $L(Y|\theta)$, i.e.:

$$p(\theta|Y) \propto L(Y|\theta)p(\theta)$$  \hspace{1cm} 4-23

Intuitively, the probability we ascribe to a given value after seeing the sample is the probability that we ascribe before seeing the sample times the likelihood that those parameters would result in the observed data.

The mean of the posterior distribution is
Train flags the importance of this mean, since from a Bayesian perspective, $\bar{\theta}$ is the value of $\theta$ which minimizes the expected cost of being wrong about $\theta$. From a classical perspective, $\bar{\theta}$ is an estimator that had the same sampling distribution as the maximum likelihood estimator (Train 2003).

### 4.3.2.1 Simulation of the Posterior Mean

Based on the previous section we define the mean as

$$\bar{\theta} = \int \theta p(\theta | Y) d\theta$$

A simulated approximation is obtained by taking draws of $\theta$ from the posterior distribution and averaging the results. The simulated mean is

$$\bar{\theta} = \frac{1}{R} \sum_{r=1}^{R} \theta^r$$

where $\theta^r$ is the $r^{th}$ draw from $p(\theta | Y)$. The standard error of the estimates is simulated by taking the standard deviation of the $R$ draws.

### 4.3.2.2 Drawing from the Posterior

To draw from the posterior we follow JMR (2007) and use Monte Carlo Markov Chain (MCMC) methods. Beforehand we present a simple example conveying the intuition behind the Bayesian methodology.

### 4.3.2.2 A Simple Bayesian Estimation

To illustrate the previous ideas we construct a simple univariate regression where $\theta$ is a scalar. Starting from the Bayes theorem

$$p(\theta | y) = \frac{p(y | \theta) p(\theta)}{p(y)}$$

$p(\theta | y)$ is the posterior distribution, $p(y | \theta)$ is the likelihood and $p(\theta)$ is the prior containing our beliefs regarding the distribution of the parameter. $p(y)$ is the marginal distribution of the data. Since it does not involve $\theta$ we can ignore it and restate Bayes' theorem as:

$$p(\theta | y) = \frac{p(y | \theta) p(\theta)}{p(y)}$$

Hence to make some inferences about $\theta$, we need a prior and likelihood. Let us first focus on the likelihood $p(y | \theta)$. This likelihood is the pdf of $y$ given $\theta$. 

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As an example, consider a simple model whereby consumption, $c$, is proportional to income, $y$:

$$c = \beta y$$  \hspace{1cm} 4-29

Assuming that for each draw $(c, y)$, each value of $c$ behaves like the realization of a normal distribution with mean $\beta y$ and variance $(1/\tau)$. For simplicity we assume homoscedasticity. If the pairs of collected $(c, y)$ are independent, the joint probability distribution of $N$ realizations of $c$ given their corresponding $y$'s is:

$$p(c \mid y, \beta) \propto \prod_{i=1}^{n} \left(\frac{\tau}{2}\right)^{1/2} \exp\left\{-\left(\frac{\tau}{2}\right)(c_i - \beta y_i)^2\right\}$$  \hspace{1cm} 4-30

Dropping all the terms not involving the parameter $\beta$ leads to the following:

$$p(c \mid y, \beta) \propto \exp\left\{-\left(\frac{\tau}{2}\right)\sum_{i=1}^{n}(c_i - \beta y_i)^2\right\}$$  \hspace{1cm} 4-31

Having defined the likelihood, we need to specify a prior for the parameter, $p(\beta)$.

We postulate through the prior below that $\beta$ could be anywhere between 0 and 2

$$p(\beta) = \frac{1}{2} \text{ for } 0 < \beta < 2$$  \hspace{1cm} 4-32

Using simulated data, and then interacting expertise (e.g. prior beliefs) with the likelihood, we obtain the following prior density:

$$p(\beta \mid c) \propto p(\beta, \tau) p(c \mid y, \beta) \propto (1/2).\exp\left\{-\left(\frac{\tau}{2}\right)\sum_{i=1}^{n}(c_i - \beta y_i)^2\right\}$$  \hspace{1cm} 4-33

which is represented in Figure 4.1:
From figure Table 4.1, two conclusions come to mind. First our beliefs that $\beta$ is superior to 1 is clearly challenged. The data mixed to our prior belief indicates that $\beta$ is more likely to be between 0 and 0.6. Secondly, while the ML estimator indicates that $\beta$ is 0.00756, incorporating the researcher's beliefs through the prior lead to an expected $\beta$ of 0.2 via the Bayesian. This latter estimate is much closer to the true value of 0.5 that was chosen to simulate the data.

Thus we have seen that the Bayesian methodology is articulated around 2 key concepts, the prior distribution of the parameters and the likelihood. While the former usually presents little difficulties, the latter can be sometimes challenging to express.

As we will see in the next section, expressing the BLP model does not escape such difficulty.

4.3.2.3 The BLP Model Through the Bayesian Method

As in GMM, we start from the RCL model in (4-4)

$$U_i = X_i \beta_i + \alpha_i p_j + \xi_i + \varepsilon_i,$$

where individuals' specific tastes $(\alpha_i, \beta_i) \sim \text{MVN}((\alpha, \beta), \Sigma)$

Assuming an extreme value distribution on $\varepsilon_i$, the individual choice probabilities are

$$s_i = \frac{\exp(X_i \beta_i + \alpha_i p_j + \xi_i)}{1 + \sum_{m=1}^J \exp(X_m \beta_i + \alpha_m p_m + \xi_m)}$$

The market shares can be retrieved through the following integration:

$$s_j = \int s_i g((\alpha_i, \beta_i) \mid (\alpha, \beta), \Sigma),$$

where $\Psi$ is the multivariate normal df of $(\alpha_i, \beta_i)$. Note that given $(\alpha, \beta)$ and the covariance matrix $\Sigma$, $s_j$ can be seen as a function of the unobservable characteristic $\xi_i$. Hence we can formulate $s_j$ as

$$s_j = h(\xi_i \mid (\alpha, \beta), \Sigma, X)$$

JMR (2007) make the point that since $\xi$ is a random variable, so is $s_j$. The key component to identify the model resides in deriving the density of $s_j$ from the prior for $\xi$:

$$\xi \sim N(0, \tau^2).$$

Inverting (4-37) and labeling the normal pdf as $\phi$ we get

$$p(\xi) = \phi(h^{-1}(s \mid (\alpha, \beta), \Sigma, X) \mid \tau^2)$$
As seen in our previous simple example under sub-section 4.3.2.1.2, a prior and a likelihood are the two essential ingredients to estimate a density of parameters consistent with the model.

Based on the above we illustrate in what follows how we can derive the density of shares by following the approach suggested by JMR (2007). We first focus on the likelihood and then the priors which we combine together recursively through the MCMC algorithm to obtain a prior distribution.

4.3.2.3.1 The Likelihood of observing the shares

A critical step in JMR (2007) is to use the Change of Variable theorem to get the joint density of shares (which is our likelihood):

\[
\pi(s_1, \ldots, s_j \mid X, \tilde{\theta}, \Sigma, \tau^2) = \Phi(h^{-1}(s_1, \ldots, s_j \mid X, \tilde{\theta}, \Sigma) \mid \tau^2) J(\xi \rightarrow \eta)
\]

\[
\pi(s_1, \ldots, s_j \mid X, \tilde{\theta}, \Sigma, \tau^2) = \Phi(h^{-1}(s_1, \ldots, s_j \mid X, \tilde{\theta}, \Sigma) \mid \tau^2) (J(\xi \rightarrow \eta))^{-1}
\]

\[
L(X, \tilde{\theta}, \Sigma) = \Phi(h^{-1}(s_1, \ldots, s_j \mid X, \tilde{\theta}, \Sigma) \mid \tau^2) (J(\xi \rightarrow \eta))^{-1}
\]

To evaluate the likelihood, we need to invert the function \( h \) in (4-39) and evaluate the Jacobian \( J \) above.

4.3.2.3.2 Computing the inverse

To invert the shares we use the contraction map suggested by Berry (1994) whereby for every given set of individual specific parameters \((\alpha, \beta)\) we can find the corresponding set of \( \xi \) that will minimize differences between simulated shares in (4-37) and observed shares.\(^76\)

4.3.2.3.3 Computing The Jacobian

The Jacobian is given by

\[
J_{\xi \rightarrow \eta} = \begin{vmatrix}
\frac{\partial s_i}{\partial \xi_i} & \ldots & \frac{\partial s_i}{\partial \xi_j} \\
\vdots & \ddots & \vdots \\
\frac{\partial s_j}{\partial \xi_i} & \ldots & \frac{\partial s_j}{\partial \xi_j}
\end{vmatrix}
\]

when assuming integration and differentiation can be interchanged.\(^77\)

\[
\frac{\partial s_j}{\partial \xi_k} = \begin{cases}
- s_j s_{ij} \cdot \Phi(\theta' \mid \tilde{\theta}, \Sigma) \ d\theta' & \text{if } k \neq j \\
(1 - s_j) \Phi(\theta' \mid \tilde{\theta}, \Sigma) \ d\theta' & \text{if } k = j
\end{cases}
\]

\(^76\) See section 4.3.1 on GMM for further details on the implementation.

\(^77\) Cf Fubini’s theorem.
and $\theta' = \alpha, \beta$, while $\bar{\theta} = \alpha, \beta$

We can write this expression as

$$\frac{\partial s_j}{\partial \xi_k} = \int f(s_j) \Phi(\theta' | \bar{\theta}, \Sigma) \, d\theta'$$

$$\frac{\partial s_j}{\partial \xi_k} = \int f \left( \frac{\exp(\delta_j + X \nu_i)}{1 + \sum_{k=1}^{n} \exp(\delta_k + X \nu_k)} \right) \Phi(\nu_i | 0, \Sigma) \, d\nu_i$$

$$\frac{\partial s_j}{\partial \xi_k} = f(\delta, \Sigma | X)$$

Through (4-45), JMR (2007) explain that given $\Sigma$ and shares, $\delta$ is uniquely determined through Berry's inversion. Indeed given the non linear parameters in $\Sigma$, we can retrieve the linear parameters analytically and simulate the shares. Through Berry's inversion and given the actual shares and $\Sigma$, we estimate the unique vector $\delta$ solving the system set in (4-15). Therefore conditional on shares, the Jacobian is only a function of $\Sigma$.

### 4.3.2.3.4 Priors

Based on the likelihood defined in (4-40) we need to focus on two priors:

$$\bar{\theta} \sim N(\bar{\theta}_0, V_\theta)$$

$$\tau^2 \sim N(\nu_0 \nu_0^2 / \nu_0^2)$$

The variance covariance matrix of the parameters allows for a cholesky decomposition

$$\Sigma = U^T U$$

Where $U$ is an upper triangular matrix

$$U = \begin{bmatrix}
\epsilon^{11} & r_{12} & r_{1k} \\
0 & \epsilon^{22} & r_{2k} \\
\vdots & \ddots & \vdots \\
0 & \cdots & \epsilon^{k\ell}
\end{bmatrix}$$

As implemented by JMR (2007), the diagonal elements enter $U$ after being exponentiated to ensure positive definiteness.

To be complete, priors on $r$ are needed:

$R_{dd'} \sim N(0, \sigma^2_{r, dd'})$ for the diagonal elements,

$R_{dk} \sim N(0, \sigma^2_{r, dk})$ for the off diagonal elements.
The joint posterior of all parameters is then given by

$$\pi(\theta, r, \tau^2 \mid \{s, X\}) \propto J^{-1}(s, X, r) \prod_{j=1}^{K} \Phi \left( \frac{h^{-1}(s \mid X, \theta, r)}{\tau} \right) \times \left[ \frac{1}{\sqrt{\tau}} \exp \left\{ -\frac{1}{2} (\theta - \theta_0)^T \Gamma^{-1} \right\} \right]$$

$$\times \prod_{j=1}^{K} \exp \left\{ -\frac{r_j^2}{2\sigma_{r, \text{diag}}^2} \right\} \times \prod_{j=1}^{K} \prod_{k=j+1}^{K} \exp \left\{ -\frac{r^2_{jk}}{2\sigma_{r, \text{diag}}^2} \right\} \times \exp \left\{ \frac{e_{\text{diag}}}{2} \right\} \times \exp \left\{ -\frac{\nu_0^2 \delta_0}{2\tau^2} \right\}$$

### 4.3.2.3.5 Posteriors Using MCMC Algorithm

The Markov Chain Monte Carlo methods, along with relentless increases in processing speed have been the backbone of the wider adoption of Bayesian Econometrics. By allowing the estimation of the posteriors through multiple draws as opposed to force to uncover exact analytical formula associated with the corresponding priors, the MCMC algorithm allows Bayesians to study problems which would have been difficult and mathematically demanding through a full analytical framework (Allenby, Rossi and McCulloch (2006)).

The Markov chain generates draws from the posterior distribution of the model parameters. Using the Bayes theorem to process the conditional draws, the intuition is as follow:

We use two sets of conditional distributions to draw from the joint posterior:

In a similar fashion with BLP, the conditional draws for $\bar{\theta}$ and $\tau^2$ are obtained by computing the mean utility $\delta_{ij} \mid X = \delta_{ij} \mid r$ and performing a Bayes regression analyses:

$$\delta_{ij} = X_{ij} \bar{\theta} + \epsilon_{ij} \sim N(0, \tau^2)$$

A random-Walk Metropolis chain is used for the draw of $r$.

$r^{\text{new}} = r^{\text{old}} + \text{MVN}(0, \sigma^2 D_r)$ where $D_r$ is the candidate covariance matrix while $\sigma^2$ is a scaling constant.

Similar to setting a covariance matrix via a 2 stages process in a classical frequentist setting, a short chain is drawn first to estimate it. Once done we can choose the scaling constant to maximize the numerical efficiency of the draw of sequences. JMR (2007) explain that since the $r$ off diagonal elements are on a different scale compared to the diagonal ones we will need two different step sizes.

### 4.3.3 Endogenous Prices & Instruments

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78 The Metropolis approach is a general useful general purpose tool. The idea is to generate a Markov chain with the posterior, $\pi(\cdot)$, as its invariant distribution by modification to a related Markov chain which is easier to simulate from compared to the conditional distribution since we might not know its analytical form. It is similar to the accept/reject method of iid sampling since we sample from a proposal distribution and then reject draws to modify the proposal distribution to achieve the desired target distribution (Rossi, Allenby and Mc Culloch (2006)).
When considering supply side dynamics, we expect that products associated with large unobserved quality are also associated with larger prices.\(^79\) Hence for both estimation methods, we can not ignore price endogeneity. Indeed the error terms are correlated with prices, which will bias the estimates.\(^80\) This endogeneity comes from the fact that market prices depend on observed and unobserved product characteristics. Any variation in those characteristics induces a variation in prices. Thus we build upon BLP (1995) and use a set of instrumental variables based on 3 subcomponents. The first one consists of worldwide production. Since Ireland is a very small economy compared to the rest of the world, we argue that worldwide production for each brand is a good proxy which captures variation in economies of scale across each brand. The second subcomponent relates to characteristics that have a statistically insignificant impact on the mean utility. Since these characteristics will still have a production cost we consider them as relevant instruments. Finally we use a subcomponent building upon the equilibrium idea behind the BLP instruments. We construct a ratio to proxy for competitive pressure on margins. This “relative density” ratio is the number of different models offered by the same firm divided by the number of models distributed by competitive firms. Hence a brand with a superior “relative coverage of market needs” is expected to be less pressurized to reduce margins compared to a brand “surrounded” by competing alternatives. On the other hand these subcomponents have no impact on the product utility and are therefore suitable instruments. In doing so we reduce the dimensionality of the instrument set thereby reducing any potential bias due to the use of too many instruments.\(^81\) Furthermore we also reduce the occurrence of singularity issues which becomes more likely when the number of instruments increases.

4.3.4 Some Practical Adjustments

The product \(j\)’s mean utility, expressed through \(\delta_j\), is a key feature of the discrete choice model estimation. As mentioned earlier we will use Berry’s contraction map to estimate the vector \(\delta\). However in this section we introduce some modifications to address computing overflow. Researchers might find these useful when using a discrete choice model, regardless of the selected methodology.\(^82\)

The computing difficulties are associated with the exponentiation of individuals’ utilities which is required to compute the simulated shares.\(^83\) In most statistical packages, obtaining a finite number

\(^79\) This is expected when reaching a market equilibrium whereby unobserved quality is costly to produce where both producers and consumers are aware of the amount of quality unobserved to the econometrician.

\(^80\) The other parameters will also be affected through the inversion of the covariance matrix – is this also a concern when using Bayesian estimation?

\(^81\) BLP use one instrumental variable per exogenous product characteristics.

\(^82\) The Contraction map is used for both the GMM and the Bayesian framework.

\(^83\) In Berry’s contraction map, the simulated shares are re-processed for each iterations of the contraction.
from an exponentiation is only possible when the exponentiated value is below 709. Any number higher than this will either return an infinite value or a numerical error.

A simple nested logit example shows why this is a problem:

\[ S_y = \frac{\exp(U_{yj})}{1 + \sum_k \exp(U_{yk})} \]

Assuming \( U_{yj} > 709 \), since \( U_{yj} \) is in both the numerator and the denominator, the computer reads the following undefined output.

\[ S_y = \frac{\text{Inf}}{\text{Inf}} \]

Such outcomes hinder our ability to recover the parameters using Berry's contraction map since the corresponding shares are a key input to the mean utility computed from (4-15).

Another issue relates to the fact that simulated market shares can not be equal to zero. In other words, at least one consumer in our sample must choose one of the products available on the market. Should this not be the case for say product \( j \), the contraction map is made unusable since the log of zero is also undefined. In Matlab, this happens when the iteration produces a mean utility lower than -705.

We must therefore deal with a boundary problem. To address it we use the scale invariance property consistent with utility theory. Concretely we add or substract a constant \( C \) without affecting the simulated shares entering the contraction map. We can verify this formally:

\[ S_y = \frac{\exp(U_{yj})}{1 + \sum_k \exp(U_{yk})} \]

\[ S_y = \frac{\exp(U_{yj}) \times \exp(C)}{\exp(C) + \exp(C) \times \sum_k \exp(U_{yj})} \]

Thus, provided we recalibrate the utility of the outside option we can add or substract any constant without affecting the convergence properties of our model. Our goal is to insure that the iterations always remain within the following range:

\[-705 < U_{yj} < 709\]

This can be achieved through the following conditional adjustments:

\[ \text{If } \max(U_{ij}) > 709 \quad U_{ij} = U_{ij} - \max(U_{ij}) + 709 \]

\[ \text{If } \min(U_{ij}) \leq -705 \quad U_{ij} = U_{ij} - \min(U_{ij}) - 705 \]
This suggests that centering the utilities can help, which is what we do. Yet there might be situations whereby the ranges of mean utilities might be wider than 1414 and the above adjustment will be inefficient. When the situation arises we decide to set problematic values to the allowable minima and maxima (-705 and 709 respectively).

We could also be tempted to use the following ratio adjustment:

\[
\text{If } \max(U_{ij}) - \min(U_{ij}) > 1414
\]

\[
U_y = U_y \times \frac{1414}{\max(U_y) - \min(U_y)}
\]

However the reason for not proceeding as above stems from the fact the logit based shares are unaffected when changing their associated level of utilities, this is not so when we proceed to a ratio adjustment:

\[
S_y = \frac{\exp(\gamma \times U_y)}{1 + \sum_k \exp(\gamma \times U_{ik})} \neq \frac{\exp(\gamma \times U_y)}{1 + \sum_k \exp(\gamma \times U_{ik})} = \frac{(\exp(U_y))^\gamma}{1 + \sum_k (\exp(U_{ik}))^\gamma}
\]

On the other hand, the trimming approach is attractive since it only affects the outliers leaving all the remaining mean utilities untouched.

Our adjustment strategy presents the double benefits of allowing the iteration to be uninterrupted should a misbehaved cycle occurs, while allowing the next cycle to self-adjust.

### 4.3.5 Computing Elasticities

One of our goals is to better understand substitution patterns of Irish Consumers when purchasing a new car. In this sub-section we present the mathematics used to reach our objective.

The elasticities of the random coefficient model are given by

\[
\eta_j = \frac{\partial s_j}{\partial p_k} \cdot \frac{p_k}{s_j} = \left\{ \begin{array}{ll}
\frac{p_k}{s_j} \sum_{i=1}^m \alpha_i s_{ji} (1 - s_{ji}), & \text{if } j = k \\
-\frac{p_k}{s_j} \sum_{i=1}^m \alpha_i s_{ji} s_{ki}, & \text{if } j \neq k
\end{array} \right.
\]

The random coefficient models offer several benefits over the Logit specifications which we used in the previous chapter of this thesis.

First, the price elasticities now depend on the price sensitivity of the individuals in the sample and not only on the functional form. Instead of being determined by the single parameter \( \alpha \), the own price elasticities are obtained by averaging the price sensitivity of the individuals in the sample. A second advantage is that the full model is not constrained by a-priori segmentation. This leads to flexible and
intuitive substitution patterns where similar individuals will tend to substitute towards the same products. Finally, the full model, by taking into account the consumer heterogeneity taste, the random coefficient logit gives another explanation (beside the price variation) to the variation of market shares across markets.

4.3.6 Benefits of the Bayesian Methodology

According to JMR (2007), the Bayesian approach, unlike GMM, is insensitive to simulation errors. The authors perform various sampling experiments and show that the Bayes estimator outperforms the GMM estimator. They also argue that an additional benefit of the Bayesian approach is the ability to conduct inference for model parameters and functions of model parameters. Therefore a natural byproduct of the MCMC simulation-based method is the possibility to construct posterior distributions for any function of the model’s parameters. In their opinion price elasticities are a much more natural summary of the parameters than the point estimates of utility weights and the covariance matrix of the random coefficient distribution. By contrast, when using the GMM estimation, the computation of asymptotic standard errors of a non-linear function of parameter estimates is often complex and computationally challenging. Indeed, Nevo (2000) uses bootstrap methods to obtain standard errors of price elasticity. Thus in the GMM, standard errors for such function of the parameters require supplemental computations outside of the estimation algorithm. On the other hand, the Bayesian MCMC approach can deliver the necessary computations in one unified computational framework.

Nonetheless, while the Bayesian methodology presents some benefits, the approach suggested by JMR (2007) does not currently include the information from demographics. Hence despite being faster\footnote{The speed of convergence depends on the number of draws. 10,000 simulations would still nonetheless take about 20 hours on a Dual Core Processor.} while also avoiding IIA, the level of insights provided is currently more limited. We will therefore extend the JMR (2007) approach to address this shortcoming in the empirical part of this chapter.

4.4 Empirical Application

In this section we first introduce useful measures regarding fit and convergence for the two estimation methods. We then explain how the standard errors were calculated. This is followed by a discussion on the use of imposing specific constraints. We close section 4.4 by checking the realism of the substitution patterns generated across each methodology to help us choose the best method.

4.4.1 Convergence
4.4.1 GMM

To assess convergence in the GMM methodology we use the J-statistic, which under homoscedasticity assumption is the value of the GMM function evaluated at the identified parameters. This statistic indicates whether the excluded instruments are valid. To assess the fit we also provide the $R^2$.

4.4.1.2 Bayes

For the Bayesian approach, we use the likelihood value as a measure of fit. To make the two models comparable we also reproduce an $R^2$. As shown in Figure 4.2, the likelihood reported for each iteration is also useful to determine the number of burn-ins required so as to use stable distributions for our analysis.

Based on figure 2 which reports the log likelihood across each draw, we decide to use 6500 draws as burn ins.\(^85\) Therefore the reported measures from the JMR methodology are based on 3350 draws\(^86\).

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\(^{85}\) Burn ins are draws that are required at the start of the sampling process to dissipate the initial condition linked to our prior. After a few draws the posterior distribution becomes stable and is no longer contaminated by the initial condition. We can then examine this distribution and better appreciate where its mass is located for each estimate.

\(^{86}\) We used 9850 draws in total.

---
A practical output of the Bayesian estimation is the distribution of the parameters of interest. Using such distribution, it is straightforward to calculate the standard errors of the estimates:

$$SE(\bar{\theta}) = \left\{ \frac{1}{N-1} \sum_{n=1}^{N} (\theta - \bar{\theta})^2 \right\}^{1/2}$$  \hspace{1cm} (4-59)

where $\bar{\theta} = \frac{1}{N} \sum_{n=1}^{N} \hat{\theta}^*$ and $\hat{\theta}^*$ is a vector of parameters for each of the N computed posteriors.

For the standard errors associated with the GMM parameters we follow Nevo (2000) and bootstrap the estimates, assuming the empirical distribution is representative of the true population distribution then the bootstrap method is adequate. Following recommendations from Efron and Tibshirani (1993), we use 100 bootstraps to which we apply formula (4-59).\(^87\)

### 4.4.3 The Estimates

The BLP estimation framework is both complex and computer intensive. Depending on the dimension of $\theta_2$, running estimations without tapping into the latest developments in optimization can take several days.\(^88\) Bearing this in mind, it is worth discussing the challenges we have met and the solutions implemented.

#### 4.4.3.1 Some useful constraints

##### 4.4.3.1.1 Avoiding Overflows

Computers are limited in the magnitude of real numbers they can output or process. When the computed number is too large for the processor to handle, this number is automatically tagged as Infinite. Likewise, if a calculation produces a too small number, this figure automatically becomes zero. On the machines we have tried, the largest computable number is $1e308$ and the smallest positive figure is around $1e-308$. While the range offered seems more than enough to perform a grid search over simple linear forms, these frontiers are easily reached when dealing with objective functions involving exponentials.

As discussed in section 4.3.4, $\exp(709)$ and $\exp(-705)$ will lead to market shares that are either undefined or null. Without any prior thinking to handle the grid search when reaching numbers

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\(^{87}\) Efron and Tibshirani show that the number of bootstrap that replicates N should be between 50 and 200 when estimating the standard error of a statistic. In most cases, taking more than 200 bootstraps is unnecessary.

\(^{88}\) Preliminary estimation using the Derivative Free Simplex method took 4 days to run using a few hundred simulated consumers.
outside the bounds \([-705, +709]\), the objective function can become undefined and the estimation fails. To reduce such occurrence, we apply the following linear constraints:

\[
Xv_2 \cdot \theta_2 < \log\left(\frac{\text{real max}}{J}\right)
\]

\[
Xv_2 \cdot \theta_2 > \log(\text{real min})
\]

*where* \(Xv_2 = [I_m \otimes X_2] \cdot [v_j]\), real max = 709 and real min = -705

\(Xv_2\) is a matrix based on the random tastes for each characteristic vector in \(X_2\) stacked up across the \(ns\) consumers and collated in \(v_j\).\(^89\) The idea is to constrain the linear part of utility to fall within a defined interval enclosed within \(\log(\text{real max})\) and \(\log(\text{real min})\). real min and real max are respectively the smallest and largest real numbers that can be exponentiated without being set to zero or infinite. This will ensure that market shares are defined across each iterations once we exponentiate the utilities. We divide real max by \(J\), to make sure that no simulated shares are equal to zero. This difficulty can occur if we divide an exponentiated utility by a number too large for the computer to process.\(^90\)

To provide further room for maneuver, we capitalize on the scale invariance property of the logit formula by reducing all the utilities of a given consumers by a constant when the simulation overflows. We retrieve the market shares by taking this constant out of the outside option’s utility, initially defaulted to zero.

\[
S_y = \frac{\exp(U_y - C)}{\exp(-C) + \sum_{n=1}^{J} \exp(U_n - C)}
\]

**4.4.3.1.2 Reducing search cost by limiting the space of potential parameters**

As seen in equations (4-7) and (4-8), some of the non-linear parameters represent the standard deviations of taste distributions and therefore need to be positive. Indeed there is no point in letting the search algorithm navigate the negative space for these parameters. We use this constraint to reduce the computing time required while also ensuring a sensible output.

**4.4.3.2 GMM vs. Bayes**

Figure 4.3 shows the mean marginal utilities conveyed by each characteristic. In this instance, the differences between GMM and Bayes’ estimation appear relatively moderate. Yet discrepancies exist.

\(^89\) \(V_j\) ‘s dimension is \((J*ns)\) by \(k\), \(k\) being the number of non-linear characteristics and \(J\) the total number of vehicles being considered.

\(^90\) This might happen if other products receive a large utility located near the upper limit of our domain.
For instance, when using GMM to identify the variable creating the largest positive impact on utility, *Performance* would be a prime candidate. This conclusion needs to be revisited when using the Bayesian estimates where *Weight* is the characteristic transferring the largest positive impact per standard deviation. While overall similarities between GMM and the Bayesian estimates might be at first reassuring, we will illustrate that including demographic variables leads to noticeable improvements. Nonetheless, the coefficients are signed in accordance with intuition regardless of the method used.

![Figure 4.3](image)

Table 4.1 reports the estimates from the two estimation procedures. For ease of comparability with the GMM estimates, we also produce a Z score for the Bayesian estimates.  

### Table 4.1a

| Mean Utility Parameters | GMM (Bootstrapped SE) | Bayes |  |
|-------------------------|-----------------------|-------|
| Coef | t-stat | Coef | Z score |
| Price | -2.43 | -3.85 | -2.72 | -2.92 |
| MPG | 0.15 | 1.16 | 0.20 | 1.31 |
| Weight | 0.25 | 0.71 | 0.81 | 2.63 |
| Performance | 1.12 | 8.52 | 0.19 | 0.09 |
| Running Cost | -0.21 | -1.61 | -0.35 | -1.65 |
| Value for Money | 0.43 | 4.24 | 0.29 | 2.70 |
| Segment Dummies | See Appendix 4 | See Appendix 4 |
| Brand Dummies | | | |
| Constant | -7.64 | -114.83 | 82.10 | 4.55 |

91 The variables have been standardized for comparison purposes and avoidance of singularity.

92 We use 20,000 draws, 2000 of which are kept for burn-in purposes. For further details see Rossi, Allenby and McCulloch (2006).

93 We randomly draw 75% of our sample 100 times.
Table 4.1ab

<table>
<thead>
<tr>
<th>Non Linear Estimates (Bootstrapped SE*)</th>
<th>GMM</th>
<th>Bayes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coef</td>
<td>t-stat</td>
<td>Coef</td>
</tr>
<tr>
<td>Price</td>
<td>0.27</td>
<td>1.77</td>
</tr>
<tr>
<td>MPG</td>
<td>0.43</td>
<td>1.27</td>
</tr>
<tr>
<td>Weight</td>
<td>0.83</td>
<td>6.17</td>
</tr>
<tr>
<td>Performance</td>
<td>1.27</td>
<td>12.00</td>
</tr>
<tr>
<td>Running Cost</td>
<td>1.33</td>
<td>6.31</td>
</tr>
<tr>
<td>Value for Money</td>
<td>0.31</td>
<td>1.75</td>
</tr>
</tbody>
</table>

Segment Dummies
See Appendix 4

Constant | 0.43 | 2.75 | 0.88 | 1.91 |

Overall $R^2$ | 97% | 92% |
J-stat (p value) | 9.98 | (12.5%) | NA |

4.4.4 Preliminary Elasticity Analysis

In this section we explore whether the different estimation methods are able to report realistic substitution patterns. As in BLP (1999) we focus our analyses on the semi elasticities rather than the elasticities. This choice allows for more leveled comparison across products since the influence of price differences between cars are better controlled. Indeed, a one percent increase on a car costing €50,000 represents quite a different amount of money compared to a one percent increase on a car costing €15,000. On the other hand the semi elasticities offer some stability by representing the percentage change in share for a €10,000 increase. The semi-price elasticity formula used is as follow:

$$\text{semi.e}_i^j = \frac{\Delta S_j}{\Delta P_j} \cdot \frac{10000}{S_j}$$

An overview regarding the substitution patterns reached through each method is provided in the Table below:

Table 4.2

<table>
<thead>
<tr>
<th></th>
<th>Lowest Semi-Elasticity*</th>
<th>Largest Semi-Elasticity*</th>
<th>Brand with Highest Elasticity</th>
<th>Brand with Lowest Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>GMM (Excl. Demog)</td>
<td>-0.91</td>
<td>-1.06</td>
<td>Mini</td>
<td>Subaru</td>
</tr>
<tr>
<td>Bayes (Excl. Demog)</td>
<td>-0.50</td>
<td>-1.30</td>
<td>Rover</td>
<td>Porsche</td>
</tr>
</tbody>
</table>

* In magnitude

We randomly drew 75% of our sample 100 times

We only report the variation explained by the linear parameters which implicitly reports how much variation is left for the non-linear parameters to explain.
Table 4.2 reflects the two graphs in Figure 4.4 below. These outputs show that while in both cases, the cross elasticities tend to follow an intuitive pattern (whereby expensive products tend to be associated with lower semi elasticities and vice versa), the GMM output strikes us by its narrow range of semi elasticities, all of them being very close to 1. This is rather unexpected for a differentiated market like the car industry. Furthermore we are surprised to see Porsche’s semi elasticity to be so close to the market average. In that regard, the Bayesian estimation displays less surprising semi elasticities, since the most prestigious brands are associated with the lowest semi-elasticities. Furthermore the Bayesian estimation leads to a wider spread of semi elasticities, which is somewhat more sensible in our opinion. Yet we are still surprised to see so many brands with semi elasticities below 1. These values are below what is usually found in the literature. BLP (1994) discloses much higher semi elasticities. While we do not exclude the possibility that the Irish market, lifted by its economic climate at the time (2003) might have been less price sensitive than in the US such difference calls for further scrutiny. Will we get larger semi elasticities when controlling for demographics? This is the question we answer in the next section, after we present the changes applied to the JMR methodology to incorporate such variables.
4.5 Incorporating the Influence of Consumers Demographics

While we have seen that the Bayesian Framework present some benefits, the current approach used by JMR (2007) does not incorporate demographic influences as in Nevo. Incorporating such information could help refining the substitution patterns while also uncovering interesting findings. For instance we might find out that older consumers with children might give less importance to performance while younger car buyers might value this feature very highly. Incorporating demographics into the current Bayesian methodology could therefore generate further insights to support policy makers interested in targeting specific segments of the populations. In this section, we extend the JMR methodology.

4.5.1 Changes applied to the Bayesian methodology

To incorporate the demographics into the Bayesian estimation we build the following utility matrix specific to each individuals, \( \mu_d \), described in (4-8)

\[
M = X \cdot \left[ \Sigma \ | \ \Pi \right] \cdot \begin{bmatrix} V \\ D \end{bmatrix},
\]

where \( V \) and \( D \) are the unobserved and observed characteristics of the \( ns \) consumers. \( \Sigma \) is the variance covariance matrix\(^{97}\) whose diagonal reflects the level of unobserved taste heterogeneity. \( \Pi \) hosts the corresponding demographic estimates reflecting the influence of income, age and having a child on the mean utility parameters entering \( \Omega_j \), in (4-50).

To estimate our system we rely on the exact same distributional assumptions than JMR (2007). We will assume the demographic parameters are drawn from the same distribution as \( r \) and therefore follow a MVN(0, \( \sigma \)). This is a convenient assumption since it allows us to make minimal adjustments to the MCMC sampler. Also for convenience and processing speed, we will nonetheless constrain the covariance matrix, \( \Sigma \), to be diagonal. \(^{98}\) However we need to update the likelihood function to account for the presence of our new parameters, \( \bar{\Pi}_{kd} \). \(^{99}\)

\(^{96}\) For instance to introduce taxes targeting specific type of households.

\(^{97}\) Its dimension is therefore \( k \) by \( k \).

\(^{98}\) JMR show that it is possible to unconstrained such matrix but since we are dealing with a single cross section we favoured a more parsimonious specification.

\(^{99}\) These are the scalar elements of \( \Pi \).

- 92 -
\[ \pi(\bar{\theta}, r, \tau^2 | \{s, X\} \propto J^{-1}(s, X, r) \sum_{j=1}^{T} \Phi \left( \frac{\hat{h}_{-1}(s, X, \theta, r)}{\tau} \right) \cdot |V|^{-1}_\theta \cdot \exp \left\{ -\frac{1}{2} (\bar{\theta} - \theta_0) V^{-1}_{\theta} (\bar{\theta} - \theta_0) \right\} \]

\times \prod_{j=1}^{T} \exp \left\{ -\frac{r_{j}^2}{2\sigma_j^2} \right\} \times \prod_{j=1}^{T} \prod_{d=1}^{D} \exp \left\{ -\frac{\bar{\pi}_{jd}^2}{2\sigma_j^2} \right\} \times (\tau^2)^{-\frac{1}{2}} \exp \left\{ -\frac{\nu \sigma_\nu}{2\tau^2} \right\} \]

4.5.2 Empirical Results when accounting for Demographics Variables

Applying the aforementioned modifications leads to the estimates in Table 4.3. We focus first on the mean utility parameters where we note that MPG is now signed negatively. This also happened with some previous nested logit specifications and could be linked to the idea that cars with lower consumption tend to be associated with lower engine sizes and therefore lower performance.

<table>
<thead>
<tr>
<th>Mean Utility Parameters</th>
<th>Bayes Demographics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef</td>
</tr>
<tr>
<td>Price</td>
<td>-6.29</td>
</tr>
<tr>
<td>MPG</td>
<td>-1.34</td>
</tr>
<tr>
<td>Weight</td>
<td>1.07</td>
</tr>
<tr>
<td>Performance</td>
<td>0.67</td>
</tr>
<tr>
<td>Running Cost</td>
<td>0.25</td>
</tr>
<tr>
<td>Value for Money</td>
<td>0.54</td>
</tr>
<tr>
<td>Firm Dummies</td>
<td>See appendix 4</td>
</tr>
<tr>
<td>Segment Dummies</td>
<td>See appendix 4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Non Linear Estimates</th>
<th>Coef</th>
<th>Z score</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Main Effects)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Price</td>
<td>0.74</td>
<td>1.28</td>
</tr>
<tr>
<td>MPG</td>
<td>1.77</td>
<td>1.49</td>
</tr>
<tr>
<td>Weight</td>
<td>1.40</td>
<td>7.84</td>
</tr>
<tr>
<td>Performance</td>
<td>0.65</td>
<td>2.14</td>
</tr>
<tr>
<td>Running Cost</td>
<td>5.72</td>
<td>0.93</td>
</tr>
<tr>
<td>Value for Money</td>
<td>2.68</td>
<td>3.76</td>
</tr>
<tr>
<td>Firm Dummies</td>
<td>See appendix 4</td>
<td></td>
</tr>
<tr>
<td>Segment Dummies</td>
<td>See appendix 4</td>
<td></td>
</tr>
</tbody>
</table>

| (Interactions)         |      |         |
| Age                    | See appendix 4 |
| Child                  | See appendix 4 |
| \( R^2 \) \(^{100} \) | 87%  |

Since price is one of the most important parameters, we explore how the estimated parametric heterogeneity of individuals' price sensitivities differs across the 3 estimation methods and whether these distributions make economic sense.

\(^{100}\) We only report the variation explained by the linear parameters which is also an indirect indication of how much variation is explained by the non-linear parameters.
Using the results in Table 4.1 and Table 4.3, we chart the distribution of price sensitivities by combining the mean utility estimates with the corresponding non-linear estimates which capture the deviations from the average market price sensitivity across the whole population. We illustrate this process with the Price and Performance estimates.

![Parametric Heterogeneity of Marginal Price Disutility](image)

**Figure 4.5**

We use the standard deviation (i.e. the non-linear parameters), $\theta$, and the corresponding mean effects, $\theta_j$, to plot the density functions in Figure 4.5. While price has a negative impact across nearly the whole population of consumers, a portion of these curves is located on the right of zero, implying that a higher price will increase the utility of some consumers. If we were to use this chart to decide between using the GMM and the Bayes’ estimation, then we lean towards the latter since it is associated with a more sensible economic output. Indeed the GMM predicts that 3.12% of the population will associate higher price with greater utility. While this is low, the Bayesian estimates outperform the GMM parameters, predicting that only 0.17% of the population will associate more expensive cars with a greater utility. The outcome is even better when interacting demographics with the cars’ characteristics since virtually no consumers associate a higher price with a higher utility. This more sensible result leads us to favour the Bayesian results incorporating consumers’ demographics.\(^\text{101}\) As such the results reported in part 4.5.2.1 onwards will be related to this specification. The same type of analysis can be made for Performance which is also associated with a significant heterogeneity parameter\(^\text{102}\). In this case we conclude that consumers are more divided

---

\(^\text{101}\) Let us keep in mind that ceteris paribus (along with some rationality assumption); when faced with 2 identical cars no one expects any consumer to prefer the more expensive one. Thus a reasonable estimation would ideally indicate that no consumer in our economy behaves in such way. This is exactly what the Bayesian estimation reports when we enrich our system with consumers demographics. As such it is our preferred estimation.

\(^\text{102}\) Hence it could be argued the GMM results invite to run a restricted version using Price and Performance as the sole heterogeneity parameters.
when it comes to the desirability of owning a performing car. A possible explanation is that performance indirectly captures a negative effect such as high taxes and insurance premium.

![Graph of Parametric Heterogeneity of Marginal Performance Utility](image)

Figure 4.6

Having seen that distributions of price disutilities are more economically consistent when incorporating the demographic variables into the Bayesian estimation, what can be said about the ranges of semi-elasticities? Are we getting values closer to the published literature? We extend the results provided in Table 4.2 to shed some light on this question:

<table>
<thead>
<tr>
<th></th>
<th>Lowest Semi-Elasticity*</th>
<th>Brand with Lowest Elasticity</th>
<th>Largest Semi-Elasticity*</th>
<th>Brand with Highest Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>GMM (Excl. Demog)</td>
<td>-0.91</td>
<td>Subaru</td>
<td>-1.06</td>
<td>Mini</td>
</tr>
<tr>
<td>Bayes (Excl. Demog)</td>
<td>-0.50</td>
<td>Porsche</td>
<td>-1.30</td>
<td>Rover</td>
</tr>
<tr>
<td>Bayes (Incl. Demog.)</td>
<td>-1.91</td>
<td>Porsche</td>
<td>-2.88</td>
<td>Daihatsu</td>
</tr>
</tbody>
</table>

* In magnitude

Table 4.4 illustrates that the semi elasticities are more pronounced when including the influence of age of head of household or the presence of children in a given household. These latest results are closer to the published ranges in the literature.

Based on the above results we therefore decide to focus our analyses of the Irish Automobile Market on the Bayesian output which factors the influence of demographic variables on tastes heterogeneity.

---

By (2004) shows some semi elasticities varying from -1.77 to -4.08. Goldberg (1995) ranging from -0.9 to -4.8. These 2 papers relate to the US market. Our results are a good match to the working paper from Baroso (2005) with elasticities enclosed between -0.89 and -2.93. These could be a more relevant benchmark since they refer to another European market which will exhibit more similar offering (Spain).
4.5.2.1 Bayesian Distributions

Another benefit of Bayesian estimation is that we can report the distributions of the non-linear parameters, $\theta^2$, upon stabilization.

Figure 4.7 provides a feel for the confidence interval associated to each of the non-linear parameters. To the exception of running cost, all the heterogeneity effects are rather well defined from a frequentist point of view. \(^{104}\)

\(^{104}\) This is confirmed through the Z-scores provided in Table 4.3.
Figure 4.7 reflects the values of $\theta_i$ across each posterior draws. This exhibit shows that a lower level of heterogeneity is expressed around the *performance* attribute. In other words one expects a less divided attitude across consumers when it comes to the enjoyment delivered by a powerful car. On the other hand, tastes for *value for money* vary widely across consumers.

This graph highlights another practical benefit from using a Bayesian output. Indeed statistically meaningful differences between heterogeneity parameters can be appreciated visually.

### 4.5.3 Analysis of Substitution Patterns

In this section we look at the semi elasticities across different levels of aggregation. We present the semi elasticities aggregated at firm and segment level through bubble charts where the size of the bubble is proportional to market share. As in section 4.4.4, we focus our analyses on the semi elasticities rather than the elasticities.

#### 4.5.2.2 Segment Semi-Elasticities

The substitutions patterns displayed in Table 4.5 are quite sensible for several reasons. First own semi elasticities are higher than any of the cross price semi elasticities. Furthermore the intra segment cross semi elasticities are also larger than any of the cross elasticities between segments. This is expected since consumers are more likely to substitute to a car from the same segment should their first choice become unaffordable. *City* and *Compact* are also strong substitutes for one another. The same

---

105 Segment, Firms and Model levels.

106 Elasticity tables are however available in Appendix.
comment applies to executive and medium sized cars. Yet the data indicates that prestigious convertibles and coupe cars are possible acceptable alternatives to both executive and 4x4 cars.

The largest level of "intra substitutions" is found within the MPV segment. This could highlight the specific needs serviced by these type of cars, thus making it more difficult for MPV buyers to substitute away.

**Table 4.5 - BAYES with Demographics**

<table>
<thead>
<tr>
<th></th>
<th>4x4</th>
<th>City</th>
<th>Compact</th>
<th>MPV</th>
<th>Exec</th>
<th>Med.</th>
<th>CV &amp; Coupe</th>
<th>Intra Segment Cross Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>4x4</td>
<td>-2.35</td>
<td>0.0013</td>
<td>0.0052</td>
<td>0.0038</td>
<td>0.0009</td>
<td>0.0011</td>
<td>0.0008</td>
<td>0.0090</td>
</tr>
<tr>
<td>City</td>
<td>0.0015</td>
<td>-2.65</td>
<td>0.0041</td>
<td>0.0008</td>
<td>0.0007</td>
<td>0.0022</td>
<td>0.0000</td>
<td>0.0093</td>
</tr>
<tr>
<td>Compact</td>
<td>0.0027</td>
<td>0.0045</td>
<td>-2.50</td>
<td>0.0018</td>
<td>0.0007</td>
<td>0.0020</td>
<td>0.0000</td>
<td>0.0061</td>
</tr>
<tr>
<td>MPV</td>
<td>0.0028</td>
<td>0.0034</td>
<td>0.0036</td>
<td>-2.69</td>
<td>0.0005</td>
<td>0.0013</td>
<td>0.0003</td>
<td>0.0145</td>
</tr>
<tr>
<td>Exec</td>
<td>0.0016</td>
<td>0.0017</td>
<td>0.0030</td>
<td>0.0001</td>
<td>-2.48</td>
<td>0.0044</td>
<td>0.0011</td>
<td>0.0049</td>
</tr>
<tr>
<td>Medium</td>
<td>0.0010</td>
<td>0.0020</td>
<td>0.0020</td>
<td>0.0002</td>
<td>0.0030</td>
<td>-2.53</td>
<td>0.0006</td>
<td>0.0078</td>
</tr>
<tr>
<td>CV&amp;Coupe</td>
<td>0.0033</td>
<td>0.0000</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0032</td>
<td>0.0008</td>
<td>-1.70</td>
<td>0.0122</td>
</tr>
</tbody>
</table>

Overall, the semi elasticity patterns shown in Figure 4.9 are intuitive since convertible cars and coupes, the most expensive cars in average, are also associated with the lowest semi elasticities while more affordable city cars represent the most price-sensitive segment.
4.5.2.3 Firms' Semi-Elasticities

Having looked at segment level substitution patterns we now focus on firms.

![Graph of Own Semi Elasticities](image)

Figure 4.10

As expected from our previous results, the semi elasticities shown in Figure 4.10 also follow an economically intuitive pattern. Indeed more expensive cars tend to be associated with lower semi elasticities while the cheapest cars are associated with higher price sensitivities. French manufacturers, Peugeot and Renaults, while enjoying large shares, are also among the most price elastic brands. Their scope for applying larger mark-ups is therefore more constrained compared to German manufacturers like BMW or Mercedes who enjoy reasonable market share in Ireland despite their higher price position. Unsurprisingly these two brands are also associated with relatively lowest semi-elasticities.

4.5.2.4 Cars Semi Elasticities

The overall positive relationship between semi-price elasticities and shares across all 827 models can be visualized from

Figure 4.11.\textsuperscript{107} When looking at semi elasticities at product level we get even closer to the magnitude published in BLP (2003) where they also included the influence of micro data.

\textsuperscript{107} The upward sloping second order polynomial trend line displayed on that chart validates our point. That line reflects about 25% of the covariance between prices and semi-elasticities.
4.5.2.5 Identifying Most Direct Competitor

An important feature from using a discrete choice model to represent a differentiated market is the ability to estimate all the cross elasticities from a limited number of parameters. Such feature can lead to some interesting insights such as identifying the “Most Direct Competitors” for each brand as shown in Table 4.6. This competitor is the one that would benefit most if the target brand was to increase its prices. In our case we see that if Alfa increases its prices by €1,000, Fiat’s share will increase by 1% versus 2.96% if Fiat were to increase its price by that same amount.

Table 4.6

<table>
<thead>
<tr>
<th>Most Direct Competitor</th>
<th>Cross Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALFA</td>
<td>FIAT</td>
</tr>
<tr>
<td>AUDI</td>
<td>MINI</td>
</tr>
<tr>
<td>BMW</td>
<td>SAAB</td>
</tr>
<tr>
<td>CHRYSLER</td>
<td>KIA</td>
</tr>
<tr>
<td>CITROEN</td>
<td>LANDROV</td>
</tr>
<tr>
<td>DAEWOO</td>
<td>HYUNDAI</td>
</tr>
<tr>
<td>DAIHATSU</td>
<td>SKODA</td>
</tr>
<tr>
<td>FIAT</td>
<td>ALFA</td>
</tr>
<tr>
<td>FORD</td>
<td>ROVER</td>
</tr>
<tr>
<td>HONDA</td>
<td>PORSCHE</td>
</tr>
<tr>
<td>HYUNDAI</td>
<td>CHRYSLER</td>
</tr>
<tr>
<td>ISUZU</td>
<td>SSANGYONG</td>
</tr>
<tr>
<td>JAGUAR</td>
<td>ISUZU</td>
</tr>
<tr>
<td>KIA</td>
<td>HYUNDAI</td>
</tr>
<tr>
<td>LANDROV</td>
<td>ISUZU</td>
</tr>
</tbody>
</table>

Unlike reduced form method like the AIDS where a parameter is needed for each model available, in a dataset like ours with 827 models collected at a single point in time such approach is clearly unfeasible and Discrete choice modelling is the only viable option.
Overall the dynamics reflected by our estimation are in line with what industry experts would expect. Indeed Asian models tend to be substitutes for other Asian brands, while premium brands such as Mercedes, BMW and Saab tend to compete together. The same comment also applies to smaller cars since Mini and Smart cross substitute each other. Figure 4.10 completes the picture and confirms that despite its high price, Porsche is among the most price resilient brands. On the other hand, mainstream brands like Fiat, Ford or Nissan would be the among the most exposed brands in case of cost increases.

4.5.2.6 Influence of Consumer Demographics on Tastes

Demographic variables not only help the estimation of sensible substitution patterns but can generate potential insights regarding consumers' purchase decisions. To this end we analyze the relevant draw sequence from the random walk chain used in the MCMC estimation and put forward some possible interpretations.

When estimating posterior probabilities via MCMC sampling, it is common practice to throw out samples from the beginning of the chain. By discounting this burn-in period, we ignore initial samples that tend to be correlated with the starting point of the chain and not representative of the probability distribution of the model we are simulating. Plotting the burn-in draws helps us to assess the relevant cut off periods beyond which we should base our estimates on since the estimation is no longer drifting (i.e. convergence has been reached). Beyond that cut off point the oscillating range provides the researcher with a better feel for the marginal impact of the interacted estimates on
consumers’ utilities. The subsequent parts provide specific comments related to these draw sequence charts.

4.5.2.6.1 Child Interactions with Firm Specific Utility

Some of the interactions between child presence in the household and utility provided by a specific Make are quite sensible. For instance the results below show that households with children get less value out of a Mini or a Smart car.

![Graph showing interactions between child presence and firm-specific utility](image)

**Figure 4.12**

4.5.2.6.2 Child Interactions with Segment Specific Utility

Consistent with the previous finding, these results suggest that parenting households allocate higher value to Multi Purpose Vehicles compared to the rest of the population. This is in line with BLP(2004)’s results who found a positive interaction between minivan and households with children.
Overall Convertibles cars and Coupes are more valued by younger buyers. This is not surprising and is similar to BLP's finding that Age and number of passengers tend to interact positively.

4.5.2.6.4 Age Interactions with Characteristics
The positive interactions between Age and MPG as well as Running cost suggest that more mature buyers tend to discriminate between long term ownership vs. purchase price. This implies that Younger Buyers are more short term focused. This hedonic tendency is validated by the negative interaction between Performance and Age while the importance of quality and safety (proxied through car's weight) is valued more by older buyers.

4.6 Conclusion, Limitations and Further Research

In this chapter we have seen that, despite using the same utility assumptions, estimation methods can have a large influence on the results. Based on the estimated cross substitution patterns and provided one is willing to supplement data and methodologies with demographic distribution, Bayesian estimation is a good alternative for our dataset. Indeed the estimated substitution patterns were in line with economic intuition while the magnitude of the elasticities were close to what is usually found in the literature. The extra complexity and efforts were therefore worthwhile. Furthermore while GMM was unable to converge to a solution when we incorporate the influence of age and the presence of a child in the household, we were able to retrieve realistic results by using a Bayesian methodology. Thus, despite the on going argument between frequentists and Bayesian researchers, the practical value of the Bayesian framework is hard to dismiss.109

109 We ran a GMM simulation inclusive of demographics for several weeks; convergence was never reached. This might be addressed by amending our optimization code. Possible options we will investigate in the near
We have also illustrated a few practical benefits related to Bayesian estimation. For instance the covariance matrix was nearly singular and therefore difficult to invert. In such context one would usually use bootstrapping methods as depicted in Nevo to compute the standard errors. However this imposes a substantial computational burden. The Bayesian option does not suffer from such requirement since the standard errors can be computed from posterior draws. The researcher will also be able to estimate at a glance the most important features impacting on demand without the need to set up any ad-hoc test. While GMM estimation will be within the comfort zone of many researchers, based on our context we conclude that the benefits brought from the Bayesian estimation outweigh the cost associated with the learning curve and required shift in state of mind.

Through this chapter we have also deepened our understanding of the car market in Ireland. We observe that some the most expensive brands, like Porsche, Mercedes or Lexus, are also among the less price-elastic brands. Likewise cheapest cars like Daihatsu, Seat or Skoda are amongst the most price-elastic brands. Thus the Bayesian approach helped us to better understand prevailing market dynamics while also avoiding the undesirable IIA property and unrealistic substitution patterns. For practitioners and researchers alike this is important since, as articulated by BLP (1994), “In an oligopoly context unreasonable patterns of demand elasticities translate into unreasonable patterns of markups.”

In terms of further research, it is worth mentioning that our MCMC algorithm struggled to reach a respectable acceptance rate. Romeo exposes a method leading to an acceptance rate of 70% using aggregate data. Therefore there would some benefits to investigating how his method could help us in improving our own acceptance rate.\(^\text{110}\)

\[^{110}\text{Currently about 15%.}\]
## APPENDIX 4:

### Firm and Segment Dummies Estimates

<table>
<thead>
<tr>
<th>Mean Utility Parameters</th>
<th>GMM (Bootstrapped SE)</th>
<th>Bayes</th>
<th>Bayes Demographics</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Coef</td>
<td>t-stat</td>
<td>Coef</td>
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<tr>
<td>Price</td>
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<td>-3.85</td>
<td>-2.72</td>
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<td>Weight</td>
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<tr>
<td>Performance</td>
<td>1.12</td>
<td>8.52</td>
<td>0.19</td>
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<tr>
<td>Running Cost</td>
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<td>-1.61</td>
<td>-0.35</td>
</tr>
<tr>
<td>Value for Money</td>
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<td>4.24</td>
<td>0.29</td>
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<tr>
<td>Alfa &amp; Fiat</td>
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<td>-2.49</td>
<td>-1.05</td>
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<tr>
<td>Audi &amp; Volkswagen</td>
<td>-0.18</td>
<td>-1.21</td>
<td>-1.14</td>
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<tr>
<td>BMW &amp; Mercedes</td>
<td>0.58</td>
<td>3.06</td>
<td>0.65</td>
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<td>Chrysler</td>
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<td>-1.86</td>
<td>-1.58</td>
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<tr>
<td>Citroen</td>
<td>0.03</td>
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<td>-0.76</td>
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<tr>
<td>Ford</td>
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<td>-0.38</td>
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<tr>
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<td>-2.62</td>
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<td>-1.31</td>
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<tr>
<td>Mini</td>
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<td>0.06</td>
<td>-1.48</td>
</tr>
<tr>
<td>Nissan, Mazda, Subaru</td>
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<td>0.01</td>
<td>-4.50</td>
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<td>Opel &amp; MG</td>
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<td>Peugeot</td>
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</tr>
<tr>
<td>Mean Utility Parameters</td>
<td>GMM (Bootstrapped SE)</td>
<td>Bayes</td>
<td>Bayes Demographics</td>
</tr>
<tr>
<td>------------------------</td>
<td>-----------------------</td>
<td>-------</td>
<td>--------------------</td>
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<tr>
<td><strong>Smart</strong></td>
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<td><strong>Suzuki</strong></td>
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<td><strong>Volvo</strong></td>
<td>0.02</td>
<td>0.24</td>
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<td>-0.56</td>
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<tr>
<td><strong>Medium &amp; Executive</strong></td>
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<td>0.17</td>
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<td><strong>Convertible &amp; Coupe</strong></td>
<td>-1.15</td>
<td>-8.56</td>
<td>-1.22</td>
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<tr>
<td><strong>Constant</strong></td>
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<td>-114.83</td>
<td>82.10</td>
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<table>
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<tr>
<th>Non Linear Estimates</th>
<th>GMM (Bootstrapped SE)</th>
<th>Bayes</th>
<th>Bayes Demographics</th>
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<tr>
<td><strong>Price</strong></td>
<td>0.27</td>
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<td><strong>Running Cost</strong></td>
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<td><strong>Value for Money</strong></td>
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<td>1.00</td>
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<td><strong>Medium &amp; Executive</strong></td>
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<td>0.00</td>
<td>0.65</td>
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<tr>
<td><strong>Convertible &amp; Coupe</strong></td>
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<td>0.57</td>
<td>1.96</td>
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<tr>
<td><strong>Constant</strong></td>
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<td>2.75</td>
<td>0.88</td>
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</table>

| Overall $R^2$          | 97%                   | 92%   | 87%                |
| **J-stat (p value)**   | 9.98                  | (12.5%)| NA                | NA    |

\[111\] We only report the variation explained by the linear parameters which is an indication of how much variation is explained by the non-linear parameters.
Segment Level Substitution Patterns (GMM and Bayes)
both excluding influence of demographics

<table>
<thead>
<tr>
<th>Table 4.7 – Semi Elasticities - GMM</th>
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<tr>
<td>4x4</td>
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<tr>
<td>-----</td>
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<tr>
<td>4x4</td>
</tr>
<tr>
<td>City</td>
</tr>
<tr>
<td>Compact</td>
</tr>
<tr>
<td>MPV</td>
</tr>
<tr>
<td>Exec</td>
</tr>
<tr>
<td>Medium</td>
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<tr>
<td>CV&amp;Coupe</td>
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<table>
<thead>
<tr>
<th>Table 4.8 – Semi Elasticities - BAYES (excl Demog)</th>
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<tr>
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<td>MPV</td>
</tr>
<tr>
<td>Exec</td>
</tr>
<tr>
<td>Medium</td>
</tr>
<tr>
<td>CV&amp;Coupe</td>
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## Elasticities

### Table 4.9 - GMM without Demographics

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<th>Compact</th>
<th>MPV</th>
<th>Exec</th>
<th>Medium</th>
<th>CV &amp; Coupe</th>
<th>Intra Segment Elasticity</th>
</tr>
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<tr>
<td><strong>4x4</strong></td>
<td>-5.00</td>
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<td>0.0027</td>
<td>0.0033</td>
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<tr>
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<tr>
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<tr>
<td><strong>MPV</strong></td>
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<tr>
<td><strong>Exec</strong></td>
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<td>0.0012</td>
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<td>-5.26</td>
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<tr>
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<td>0.0032</td>
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<td>-3.01</td>
<td>0.0014</td>
<td>0.0039</td>
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<tr>
<td><strong>CV&amp;Coupe</strong></td>
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<td>0.0018</td>
<td>0.0028</td>
<td>0.0015</td>
<td>0.0052</td>
<td>0.0038</td>
<td>-7.06</td>
<td>0.0029</td>
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</table>

### Table 4.10 - BAYES without Demographics

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<th>Compact</th>
<th>MPV</th>
<th>Exec</th>
<th>Medium</th>
<th>CV &amp; Coupe</th>
<th>Intra Segment Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>4x4</strong></td>
<td>-4.88</td>
<td>0.0012</td>
<td>0.0032</td>
<td>0.0047</td>
<td>0.0033</td>
<td>0.0026</td>
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<td>0.0118</td>
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<td>0.0036</td>
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<td>0.0029</td>
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<tr>
<td><strong>Compact</strong></td>
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<td>0.0030</td>
<td>-2.39</td>
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<td>0.0016</td>
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<td><strong>MPV</strong></td>
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<td>0.0020</td>
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<td>0.0028</td>
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<td>0.0036</td>
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<tr>
<td><strong>Exec</strong></td>
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<td>0.0022</td>
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<td>0.0050</td>
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<td><strong>CV&amp;Coupe</strong></td>
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<td>0.0016</td>
<td>0.0026</td>
<td>0.0010</td>
<td>-3.92</td>
<td>0.0058</td>
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5

CONCLUSION

5.1 Findings on the Industry

The Irish Automotive industry is important and interesting not only because of its size but also because of its features that make it an informative industry to analyse from an economic perspective. In chapter 1, we present these features and highlight the key stakeholders with an interest in that market. The government, for instance, raises more than a billion Euros each year through taxes imposed on new cars sold in Ireland.

In chapter 2, we describe the unique dataset purposefully constructed to study this market. The quite high level of concentration prevailing in the market is also discussed. Based on preliminary industry concentration analyses, we conclude in this chapter that existing public concerns regarding collusion may be justified, especially for segments like convertibles or executive cars. If industry concentration has an effect on profitability we conjecture that higher margins are expected in these two segments.

In chapter 3, we test the collusion hypothesis by following the steps of BLP (1995). We implement a simultaneous model to describe both consumer preferences and firm conduct. Using Bertrand-Nash assumptions regarding the observed equilibrium in 2003, we test several price coordination structures. Using the Vuong test, we do not have enough evidence to support collusion between car importers. Instead we find that the data are more supportive of a pricing coordination across brands when these brands were owned by the same corporation (e.g. Volkswagen and Audi or Peugeot and Citroen). Assuming such coordination is only happening at a manufacturer level this would still be within the legal boundaries of competition law.\textsuperscript{112}

Using the scenario most supported by our data we extract the marginal cost for each model. Given marginal costs the industry profits are easily calculated for each brand. In doing so we are able to validate our hypothesis regarding higher profitability for convertibles and coupes as well as executive cars. Overall profits were estimated at more than 800 million Euros across the whole industry with Toyota, Mercedes, Nissan and Ford capturing the largest share of profit. In the second part of Chapter 3 we extend our analysis beyond profitability and market power to concentrate on the transition regime that was introduced prior to the implementation of the VRT based on carbon dioxide emission as opposed to engine size. Using the costs and the marginal effect of price on utility estimated in the first part of chapter 3 we simulate the new equilibrium reached by solving for the new mark-ups in

\textsuperscript{112} At the time of writing we learned that Ford dealers (which are within the top most profitable companies according to our results) were convicted of price coordination in 2007 while the Citroen Dealers Association were being heard in 2008 for the alleged cartel activity of its members (Gray and McCloughan 2008).
the first order condition associated with profit maximization. Interestingly, under our setting, we found that the market is expected to expand due to the low taxation on smaller cars. This was however mitigated by a contraction in demand for bigger cars. The net effect for both consumers and firms was still better than before the tax reform. The new equilibrium forecasts a five percent drop in government revenue. This decline is driven by the reduction in demand for larger cars. Our recommendation therefore would have been to introduce a lower tax rate on higher-end cars to minimize its impact on tax revenue while also benefiting from market expansion.

While rich in its content the analysis from chapter 3 has some limitations, some of which are addressed in chapter 4. Specifically, within a logit model, cross substitution patterns are mostly driven by market shares. This leads to cross elasticities that ignore the influence of characteristics between cars and the idea of cross elasticities between similar cars. Furthermore, because market shares are quite small at a product level, both the logit and nested logit formulae tend to exhibit larger elasticities for more expensive cars, which is against the economic intuition that the cheapest cars are usually bought by consumers with a more limited income who are therefore expected to be more price sensitive. This technicality can have deep consequences when stakes are high such as during a merger case. Using the more sophisticated random coefficient logit model to describe consumers with different tastes for both observed and unobserved characteristics, we are able to incorporate the idea that similar people with similar tastes will be likely to have the same preference rankings and will therefore substitute towards the same products.

We took this opportunity to compare the outcome from the original GMM strategy to a Bayesian framework. While both methods are computer intensive we investigate the value of the Bayesian estimation in a more sophisticated setting where we interact demographics with characteristics to allow for richer consumer heterogeneity, not only at the residual level but also across each characteristic.

Within this setting we draw attention to the value of using a Bayesian approach since it leads to a stable distribution of estimates while the GMM method does not converge. In addition, the cross elasticities estimated with the extended Bayesian methods are the most sensible. Our results show that high end cars like *Porsche* are associated with lower price elasticities while cheaper brands have the highest price elasticity. Based on this outcome we provide some justification for researchers to consider the Bayesian estimation in conducting analyses of this kind.

Incorporating demographic information about consumers allows for more insightful analysis of the market. For instance we find some evidence that older consumers are more interested in ownership costs than performance. This type of finding could be useful for creative policy makers wanting to discriminate across population segments in designing effective taxation policy by, for instance, introducing a tax based on the vehicle performance rather than its consumption in an attempt to reduce the number of car accidents generated by younger drivers driving more powerful vehicles, or
by reducing the road tax on MPVs to favour consumers with children regardless of their work situation.\textsuperscript{113}

5.2 Methodological contributions

Chapter 4 was an opportunity to extend JMR’s Bayesian estimation to incorporate the influence of demographic variables on taste heterogeneity. This was done through a modification of the likelihood formula. While very computer intensive we would not have extracted the richer and more sensible substitution patterns found if GMM was our only option. To the best of our knowledge this is the first time that the JMR Bayesian estimation has been used with a mix of macro and micro data.

5.3 Limitations and Further Research

While most of our findings rely on sophisticated methods, we must mention a few limitations. For instance, the fact that we did not include income in our Tax reform simulations reduces the model’s capability of adapting to a different economic climate. This is not irrelevant given the current recession. However, it would be interesting to extend our database to incorporate the impact of the economic downturn on both the industry and the associated Tax revenue. Our findings on collusions are limited since the model implemented in chapter 3 does not allow us to discriminate between manufacturers and car dealers. This limitation hinders our ability to explore the possibility of collusion at dealership level. Villas-Boas (2007) is able to back out retail level markups across the distribution channels without access to wholesale data. Thus the current research would benefit from replicating her method which assumes a sequential pricing game based on a structural model of nonintegrated vertically related markets. Long term dynamics are not captured either, yet they can be very important. For instance, with the global taxation shift on CO\textsubscript{2} emissions, one can safely expect the industry to adapt. Therefore extending the estimation to a more dynamic setting would lead to some interesting insights regarding the entry and exit of car models. However to implement Villas-Boas’ methodology we believe that dealer level sales data would need to be made available.

\textsuperscript{113} Such a tax could benefit non-working mothers for instance.
<table>
<thead>
<tr>
<th>Term</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-60</td>
<td>Indicates acceleration capability of the car, as measure by how long it takes to go from 0 to 60 miles per hour.</td>
</tr>
<tr>
<td>Auto</td>
<td>A dummy equal to 1 if the car is equipped with automatic gearing, see 2.3.1.</td>
</tr>
<tr>
<td>BLP</td>
<td>Refers to the Berry, Levinsohn and Pakes.</td>
</tr>
<tr>
<td>C3</td>
<td>The share of the market or segment captured by the 3 largest manufacturers, see 2.4.3.</td>
</tr>
<tr>
<td>C5</td>
<td>The share of the market or segment captured by the 5 largest manufacturers, see 2.4.3.</td>
</tr>
<tr>
<td>CBG</td>
<td>Car Buyer Guide, see chapter 2.2.5 and relevant variables extracted from that magazine presented in part 2.3.</td>
</tr>
<tr>
<td>CC</td>
<td>Engine’s cubic capacity see chapter 2.2.</td>
</tr>
<tr>
<td>Coef.</td>
<td>Coefficients, see for instance Table 4.3.</td>
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<tr>
<td>CPI</td>
<td>Consumer Price Index</td>
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<td>CSO</td>
<td>Central Statistic Office, see chapter 2.2.</td>
</tr>
<tr>
<td>CV&amp;Coupe</td>
<td>Convertibles and Coupes, see example in 2.4.1.</td>
</tr>
<tr>
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<td>Heterogeneity parameters corresponding to the demographic variables extracted from the Household Budget Survey. See Figure 4.5.</td>
</tr>
<tr>
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<td>Exclusive, see Table 4.4.</td>
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<tr>
<td>Exec</td>
<td>Executive cars, see example in 2.4.1.</td>
</tr>
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<td>General Method of Moments, see chapters 1.4.1, 3.3.1 and 4.3.1.</td>
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<td>HP</td>
<td>Engine’s horsepower, see chapter 2.2.</td>
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<td>IIA</td>
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</tr>
<tr>
<td>JMR</td>
<td>Refers to the Bayesian estimation of the BLP model presented in chapter 4 and following Jiang, R., Manchanda, P. and Rossi, P. (2009).</td>
</tr>
<tr>
<td>Landrov</td>
<td>Land Rover, see Table 4.6.</td>
</tr>
<tr>
<td>MCMC</td>
<td>Monte Carlo Markov Chain, see 4.3.2.1.2 and 4.3.2.3.5.</td>
</tr>
<tr>
<td>Med.</td>
<td>Medium cars, see Table 4.5.</td>
</tr>
<tr>
<td>Merc</td>
<td>Mercedes, see Table 4.6.</td>
</tr>
<tr>
<td>Mits.</td>
<td>Refers to the German brand Volkswagen.</td>
</tr>
</tbody>
</table>
ML  Maximum Likelihood, see Figure 4.1.
MPG  Miles per Gallon, see chapter 2.2.
MPV  Multi Purpose Vehicle, see example in 2.4.1.
MVN  Multi-Variate Normal distribution, see equation 4-34.
OMSP  Open Market Selling Price, which is the retailer price exclusive of VAT and VRT, see equation 3-64.
Pdf  Probability density function, see Figure 4.1.
Qty  Stands for discrete quantities of cars sold, see Table 3.14.
R&D  Research and development, see 3.6.
RCL  Random Coefficients Logit model, see 4.2.
SE  Standard Error see equation 4-59 or Table 4.1.
Seg.  Stand for Segments parameters, see Table 2.1 and corresponding estimates in Table 3.4 and
Sigma  Within group correlation from the nested logit estimated from equation 3-47 and corresponding parameters presented in Table 3.4.
SIMI  Society of Irish Motor Industry, see chapter 2.2.
SUV  Sport Utility Vehicle, see example in 2.4.1.
VRT  Vehicle Registration Tax, see chapter 2.2.1 as well as Table 3.11 for old and amended rates.
VW  Refers to the German brand Volkswagen.
BIBLIOGRAPHY


