Essays on the Economics of Energy Efficiency

Evidence from residential dwellings and commercial data centres

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by

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Bryan Coyne

Bryan Coyne
29th October 2020

Abstract

Global economic growth since the Industrial Revolution has been facilitated, in large part, by the increased use of natural resources as energy in the production process. This has revolutionised how society functions. Historical energy use has accelerated climate change, which has dire implications for future economies, environments and ecosystems. Governments have attempted to enact policies that attempt to avoid this crisis, by seeking to lower energy use, increase renewable energy generation and by improving energy efficiency.

Research has noted significant variation in the effectiveness of energy efficiency policies. It has noted several market-based and behavioural factors that help to explain the energy use of consumers and firms. The central concept of many energy efficiency policies is to reach the socially optimal solution that considers the externality associated with energy use.

This thesis studies the effectiveness of energy efficiency policies in the residential sector and the benefits of energy efficiency for data centres. The former is important due to the ambitious plans to decarbonise the residential sector. The latter topic is relevant due to the rapid and under-researched evolution of new, large scale industry that has the potential to compromise national efforts towards combating climate change.

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There are no words that truly reflect my gratitude for my mother, Mary Coyne. I hope this work validates her commitment to education and reflects the value she places in being a person of high integrity, above all else. None of this would be possible without you.

This thesis reflects the same work ethic and passion that my siblings Gavin, Elain, Susan, Colin, Karen and Allan have demonstrated in their lives. I have been fortunate to follow your lead. I also wish to thank the Finnegan family, for their support and passion for learning. And to Bailey, the best friend a man could ask for.

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Summary

This thesis explores four distinct questions related to the adoption and effectiveness of energy efficiency. This work features an empirical focus and applies a range of econometric tools to investigate each research question. The choice of research questions considers energy efficiency through the distinct lenses of the residential sector and commercial data centres. This dual perspective is important as homeowners and firms face unique challenges and warrant attention, with no silver bullet that represents a solution for all markets. Table I summarises the four papers in this thesis and details the research questions, method and the author's contribution.

Chapter 1 introduces the dissertation, including a high-level background to the research and a preview of the specific research questions explored in this dissertation. It discusses the critical role of energy use in historical economic development, how this activity has contributed to the urgent issue of climate change and how energy efficiency may represent a pathway to reducing emissions without compromising on economic output.

Chapter 2 presents the first article of the dissertation and examines the critical role of Energy Performance Certificates (EPC) in guiding residential energy efficiency policy and tests the extent to which they accurately reflect occupant energy use behaviour. It uses a unique dataset that merges metered electricity and gas use data and EPC information for a general housing sample over multiple years. It performs a range of regression techniques to investigate differences in actual and theoretical energy use and to understand influential drivers of differences.

The results of this paper indicate that there is a weak relationship between a dwellings EPC and occupant energy use. There is evidence of an Energy Performance Gap, with an average deficit of actual energy use between 8-17% below the adjusted EPC level. It highlights significant heterogeneity in the size of the Energy Performance Gap across dwellings. Individuals in the lowest efficiency dwellings feature an average difference ranging from -15% to -56% of the relevant EPC. Conversely, individuals in the most efficient dwellings display higher-than-theoretical energy use, with average differences ranging from 39% to 54% of the relevant EPC. This sounds a note of caution for policymakers that expect a theoretical EPC to translate to energy savings. This paper has been presented at multiple conferences and is currently under review (R&R) in *Energy Efficiency*.

Table I: Summary of research studies

Title	**Mind the Energy Performance Gap: Testing the Accuracy of Building Energy Performance Certificates in Ireland**	**Evaluating a national residential retrofit scheme using whole-home energy use data**	**A Model of Technology Diffusion to Forecast Data Centre Electricity Use**	**The multiple benefits of large-scale energy efficiency technology adoption**
Research questions	What difference, if any, exists between measured whole-home energy usage and the household EPC rating? How much of the variation in measured whole-home energy use is explained by the household EPC rating, key dwelling features and seasonality?	Does a subsidised home energy retrofit lower measured whole-home energy usage? Does the household EPC rating accurately reflect measured whole-home energy use for homes that receive a subsidised retrofit? What is the difference between the expected and actual upfront value for money of a subsidised retrofit?	What is the expected impact of energy efficiency adoption in a large industrial end use (data centres) on electricity demand when the extent of technology adoption features significant uncertainty?	What are the energy savings associated with adoption of a large-scale energy efficiency technology for data centre cooling? What are the energy savings associated with adoption of a large-scale energy efficiency technology for a district heating network? What are the savings associated with adoption of a large-scale energy efficiency technology for a national transmission system?
Methodological approach	Econometric analysis (Linear regression, T-Test of means)	Econometric analysis (Fixed effects panel regression, T-Test of means, investment analysis)	Technology diffusion modelling; energy demand forecasting	Plant and market-level energy demand forecasting, Power systems analysis
Authors	Bryan Coyne, Eleanor Denny	Bryan Coyne, Eleanor Denny	Bryan Coyne, Eleanor Denny	Bryan Coyne, Eleanor Denny, Desta Fitiwi
Own contribution	Bryan Coyne led the data analysis and manuscript drafting. He received valuable contributions and feedback from his co-author throughout.	Bryan Coyne led the data analysis and manuscript drafting. He received valuable contributions and feedback from his co-author throughout.	Bryan Coyne led the data analysis and manuscript drafting. He received valuable contributions and feedback from his co-author throughout.	Bryan Coyne led the data analysis and manuscript drafting. He received valuable contributions and feedback from his co-author throughout. Desta Fitiwi facilitated the power systems analysis.
Publication status (as of October 2020)	Currently at Revise and Resubmit (R&R) status in *Energy Efficiency*	Submitted to *Energy Policy*	Submitted to the *Technological Forecasting and Social Change*	Submitted to the *Journal of Cleaner Production*

Chapter 3 presents the second paper of the dissertation and investigates the effectiveness of a national subsidy towards domestic energy efficiency measures. It uses a unique dataset that merges metered electricity and gas use data with retrofit and EPC information for a general housing sample over multiple years. A novel contribution is the ability to study behavioural whole-home energy use for households that received a subsidised improvement before the observation period. It applies fixed effects linear regression to account for household- and time-related heterogeneity.

Results show that retrofits reduce energy use by 943 kWh/year, on average, after accounting for customer- and period-related heterogeneity. However, the magnitude of this effect varies depending on the measures received, with some leading to higher energy use post-retrofit. Additional results suggest that retrofits offer better value for money when measured by actual changes in energy use, instead of a measure based on the change in EPC. Although retrofit subsidies may be a productive policy lever, this paper suggests it may lead to unintended consequences, such as an outcome where households avail of the subsidy to purchase an energy efficiency technology that they intended to purchase in the absence of any subsidy. This undermines the intention of such subsidies. This paper has been presented at an international conference and is currently under review in *Energy Policy.*

Chapter 4 presents the third paper and focuses on the significant energy use within the commercial data centre sector and quantifies the scope for improving energy efficiency. A key contribution of this chapter is the development of a technology-agnostic model of technology diffusion to aid decision making under uncertainty where public data are limited. This is particularly important given the degree to which information asymmetry is pervasive in many sectors and can often hinder the adoption of energy efficiency. Results show that technology adoption could lower national electricity demand by between 0.81% to 3.16% by 2028, depending on whether the technology could be adopted by data centres that are already operational. This paper has been presented at multiple conferences and is currently under review in the *Journal of Cleaner Production.*

Chapter 5 presents the fourth and final paper, which quantifies the key economic benefit in terms of energy use for a commercially available large-scale energy efficiency technology that converts renewable electricity into cooling supply for data centres while also providing hot water supply. This chapter represents an example of technology has suffered from a lack of adoption as it provides multiple benefits to private and public stakeholders.

It combines a unique dataset of information on data centre capacity with technical parameters of the technology to develop market-level forecasts. The public benefits of technology adoption are quantified using a power systems model of the national transmission system. Results illustrate the potential for energy efficiency to deliver real energy savings at the firm and national levels, contingent on technology adoption.

Results find that technology adoption could lower sectoral energy use by 26% and supply 12.40 TWh of hot water for use in a 4^{th} Generation district heating network in Ireland over the 2019-2028 period. A 2030 power systems analysis suggests that adoption can reduce renewable electricity capacity requirements by 6.92% and lower system-wide emissions by 3%. Results highlight the potential for technology adoption to enhance sector coupling and deliver benefits in multiple sectors. This paper co-authored with Dr. Desta Fitiwi of the ESRI is currently under review in the *Journal of Cleaner Production.*

Chapter 6 concludes the dissertation and frames the research within the broader context of energy efficiency. Limitations of the research are highlighted and potential areas for future research are detailed.

Publications Arising from Thesis

Journal Papers

- B. Coyne & E. Denny, “Mind the Energy Performance Gap: Testing the Accuracy of Building Energy Performance Certificates in Ireland”, *Energy Efficiency (revise and resubmit).*
- B. Coyne & E. Denny, “Evaluating a national residential retrofit scheme using whole-home energy use data”, *Energy Policy (in review)*
- B. Coyne & E. Denny, “Applying a Applying a Model of Technology Diffusion to Forecast Future Data Centre Electricity Use”, *Journal of Cleaner Production (in review)*
- C. Coyne, E. Denny & D.Z. Fitiwi, “The potential benefits of wide scale adoption of energy efficiency technology in data centres”, *Journal of Cleaner Production (in review)*

Conference Papers

B. Coyne & E. Denny, “Mind the Energy Performance Gap: Testing the Accuracy of Building Energy Performance Certificates in Ireland”

- Irish Postgraduate and Early Career Economics Workshop. 7th June 2019, Galway, Ireland.
- Irish Economic Association Conference 2019. 14th May 2019, Cork, Ireland.

B. Coyne & E. Denny, “Evaluating a national residential retrofit scheme using whole-home energy use data”

- 13th International Workshop on Empirical Methods in Energy Economics (EMEE). 13th January 2020, Zurich, Switzerland.

B. Coyne & E. Denny, “Applying a Applying a Model of Technology Diffusion to Forecast Future Data Centre Electricity Use”

- International Association for Energy Economics (IAEE) European Conference 2017. Vienna, Austria. 6th September 2017.
- Energy Systems Integration Partnership Programme (ESIPP) Annual Conference 2017. Dublin, Ireland. 23rd October 2017.

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Chapter 1: Introduction

1.1 Energy and the global economy

Energy use has influenced the global economy for centuries. At a fundamental level, Ayres & Kneese (1969) note that all economic activity is constrained by the laws of thermodynamics and the conversion of matter. On this matter, Stern (1997) asserts that energy is an essential factor of production, where any sort of output involves work by a factor of production. Malthus (1798) characterised the pre-industrial economy as a difficult balance between achieving simultaneous population and agricultural output growth. Wrigley (1990) noted that the Industrial Revolution was fuelled, in part, by fossil fuel use that relaxed constraints on energy supply and spurred economic growth.

Following this period, there was a profound shift in the global economy. McNeill (2000) notes how the Industrial Revolution helped facilitate a doubling of population in Africa, Asia and Europa and a five-fold increase in the Americas, Australia and Oceania from 1850-1950. More recent work by Dalgaard & Strulik (2007) prove a link between energy supply and long term growth in technological progress. In particular, the influential role of coal in global economic development during the period 1800-1970 is established by Froeling (2011).

Through this lens, the classical Malthusian Trap was overcome due in part to the extraction of natural resources and its conversion into energy for use in the production process. The use of natural resources as energy combined with technological progress ushered in an era of unprecedented economic development, helping make more productive workers, better learners and to change how individuals interact with the world.

In the twenty-first century, it has become apparent that future generations will pay the price for the fossil-based economic growth of recent centuries. The United Nations Intergovernmental Panel on Climate Change states that "human activities are estimated to have caused approximately 1.0°C of global warming above pre-industrial levels … Global warming is likely to reach 1.5°C between 2030 and 2052 if it continues to increase at the current rate" (UN-IPCC 2018). In one example, a spatial macroeconomic analysis of the future impact of climate change suggests that global GDP would fall by 0.26% through changes in the ten most popular crops alone (Costinot et al. 2016).

Through an economic lens, Stern (2008) noted that “greenhouse gas emissions are externalities and represent the biggest market failure the world has seen”. In particular, it has been noted that economic activity since the industrial revolution did not bear the full cost of production because firms did not internalise the social costs associated with air and water pollution (Andrew 2008; N. Stern 2006). Climate change has the unique combination of global causes and consequences that are long-term, persistent and uncertain (N. Stern 2006).

A global problem requires a global solution. Every country (with some notable abstentions) has agreed to strive to limit global temperature increase to two degrees Celsius (United Nations 2015). The European Union has been progressive in this area, with member-specific targets to increase energy generation from renewable sources, reduce emissions and increase energy efficiency by the year 2030 (European Commission 2018) on the pathway to a net-zero carbon economy by 2050 (European Commission 2019a). 2030 climate targets include i) sourcing 32% of the energy mix from renewable sources, ii) reducing GHG emissions by 40% from 1990 levels and iii) a 32.5% improvement in energy efficiency, relative to a 2007 forecast (European Parliament 2018). Technologies that improve energy efficiency typically serve a dual purpose by enabling a transition towards a low-carbon economy.

This thesis explores four distinct questions related to the effectiveness of selected energy efficiency technologies and policies. Understanding their potential is critical to understand how energy efficiency can improve societal welfare and help to combat climate change. Specifically, it studies the accuracy of policy tools designed to increase awareness of residential energy efficiency (Chapter 2), the adoption of residential energy efficiency technologies through a subsidised retrofit scheme (Chapter 3), the scope to improve commercial data centre energy efficiency under uncertainty (Chapter 4) and the potential for commercially-ready technology to improve data centre energy efficiency while supporting decarbonisation efforts in the electricity and heating sectors (Chapter 5).

This work is motivated, in large part, by the substantial efforts of governments, firms and consumers to lower their energy demand while also maintaining a high standard of living. It identifies policies and technologies that are effective, highlights areas for improvement and details the potential of emerging technologies and industries that could play a key role in decarbonising the economy.

1.2 Energy efficiency - Doing more with less

Improvements in energy efficiency and its widespread adoption could help to decouple economic growth from energy use. It is a good example of the type of endogenous long-run economic growth discussed by Romer (1990), where technological innovations provide spill-over effects to society. With the lives of future generations at risk, energy efficiency serves a vital public good.

Analysts are enthusiastic about the potential of energy efficiency. McKinsey (2010) assert that energy efficiency represents about 40 percent of the potential to reduce global greenhouse gas (GHG) emissions at a cost of less than €60 per metric tonne of carbon dioxide equivalent. In many cases, energy efficient technologies feature a negative net present value - paying for itself over time. Jaffe and Stavins (1994a) highlight how energy efficiency is often a pathway to reach optimal resource allocation. Like an athlete relegated to the bench, it is difficult for energy efficiency to have a real impact if it is not being used. Substantive change only occurs when innovations are widely adopted. The International Energy Agency assert that energy efficiency has had limited uptake to date due to the ongoing use of less efficient technologies, a lack of effective policy and limited investment (IEA 2020).

The Energy Efficiency Gap (Jaffe and Stavins 1994b) represented one of the earliest theories explaining why energy efficiency is under-adopted at the societal level. If an energy efficient good has a positive net present value, then why is it not adopted by consumers? Subsequent research has worked to understand why this occurs, with a variety of evidence across contexts. Gerarden et al. (2017) synthesise all of the empirically observed phenomena and assert that the Energy Efficiency Gap is comprised of market failures (examples include principal-agent issues, asymmetric information and liquidity constraints that all limit technology adoption), behavioural factors (e.g. salience and inattention) and model measurement error (e.g. incorrect assumptions regarding costs, benefits or consumer behaviour patterns). Allcott & Greenstone (2012) delve into the latter of these issues by theorizing that the size of the Energy Efficiency Gap is overstated due to overly-optimistic engineering-based models of savings. This helps to rationalise, in part, why the level of technology adoption of energy efficiency lags behind a social optimum.

Jaffe and Stavins (1994b) highlight the important role of public policy in helping to spur the adoption of energy efficiency. Such government intervention is commonly observed in the residential sector. Examples include subsidies towards adoption of energy efficient technologies (Fowlie et al. 2018), carbon taxes levied on the purchase of certain fuels (Lin and Li 2011), taxes on energy bills to aid development of renewable energy generation (Lynch and Devine 2019) and the deployment of smart home metering to improve residential demand side management (Di Cosmo et al. 2014).

Evidence from the residential sector on the effectiveness of such energy efficiency policies is situation-specific and mixed (Allcott and Greenstone 2012). Recent examples highlight the unintended outcomes of certain policies. For example, customers that would have upgraded their home heating system without a subsidy, use the subsidy to purchase a larger-than-necessary system that negated the energy savings of improved energy efficiency (Alberini et al. 2016). In other cases, the adoption of energy efficient technology can reduce a 'rebound' effect, where the lower effective price of heating induces a behavioural response in end-users, resulting in increased energy use (Heesen and Madlener 2018; Sorrell et al. 2009). There is an extensive literature on the 'rebound' effect from a variety of contexts, where the adoption of energy efficiency causes consumers to change their energy use. Estimates of the extent of rebound vary, with a bibliographic review noting an average long-run rebound of 30% (Sorrell et al. 2009). Rebound effects have the potential to undermine the intent of policies that subsidise retrofit (Gerarden et al., 2015), with the context-specific nature of rebound making it difficult to correctly formulating energy efficiency policies (Aydin et al. 2017).

Although the presence of rebound complicates forecasts of progress towards national energy efficiency targets, it is still an intended outcome. Consumers increasing energy use after receiving a subsidy is often one of the intentions of a residential energy efficiency policy. This is especially the case for socially vulnerable occupants in low-efficiency dwellings that traditionally under-heated their homes (Coyne et al. 2018; Fowlie et al. 2018; Sunikka-blank and Galvin 2012). As an example, Coyne et al. (2018) find an average 30% shortfall between the expected and actual change in energy use for a sample of social housing tenants. This emphasises the important role of occupant behaviour in achieving expected energy savings and may influence the effectiveness (and motivation) for similar policies in the future.

Subsidising energy efficiency presents a pathway for policymakers to improve societal wellbeing by improving access to the multiple benefits associated with improving energy efficiency. However, it is important for policymakers to understand the responses of end-users to improvements in energy efficiency, accounting for the Energy Efficiency Gap, issues such as rebound (considered in Chapter 3) and differences in actual consumer behaviour and theoretical assumptions (considered in Chapter 2) may result in a lack of achievement towards EU-level energy efficiency targets. This has wider consequences for national efforts to combat climate change and can result in substantial penalties.

The collective body of evidence to date helps to advance our understanding of what policies are effective. Helm (2010) sounds an important note of caution on the effectiveness of policymakers, noting that although governments attempt to formulate effective climate policy, interventions often lead to suboptimal policies. He demonstrates this for the cases of economic rent capture in emissions trading schemes.

Through this lens, there is a need for research that attempts to critically evaluate the actual benefit of energy efficiency (in terms of changes in energy demand pursuant to national targets) and to understand the factors driving its adoption. A failure to understand current limitations across the entire built environment (including residential and commercial agents) makes it challenging to correctly calibrate prescribe policies that help to fulfil national responsibilities to tackle the global issue of climate change.

1.3 Thesis motivation and chapter previews

Chapter 2: Testing the accuracy of residential Energy Performance Certificates

In an effort to draw awareness to energy efficiency and the often invisible nature of energy use in buildings, many countries have modelled the expected energy use of buildings (European Parliament 2018). In many cases, this has led to the creation of Energy Performance Certificates (EPCs), which denote a building's performance. These labels are often required for property sales and leases (European Commission 2018). Prior studies have found evidence of an Energy Performance Gap, with significant differences exists between actual energy use and the EPC-predicted level (De Wilde 2014). Evidence into the EPG suggests that policies aiming to reach a certain EPC standard may not achieve the expected energy savings (Cozza et al. 2020; Gram-Hanssen and Georg 2018; Zou et al. 2018).

This is the first study that tests for the presence of an EPG using a measure of whole-home energy use for a non-social housing sample of 9,923 households that do not receive a retrofit. The key contribution of this paper is the combination of i) the analysis of whole-home energy use, ii) for a non-social housing sample that iii) does not feature behavioural changes that would be induced by retrofit. Previous studies have considered one or two of these aspects, but this is the first study combines all three to overcome limitations of previous studies (Cozza et al. 2020; van den Brom et al. 2018).

The key insight from this study is the striking lack of variation in average actual energy use across the sample (457 kWh/year). This suggests that occupant demand for energy may not be as responsive to dwelling energy efficiency. Results find evidence of an Energy Performance Gap, with an average deficit of between 8-17% below theoretical energy use. However, there is significant heterogeneity in the direction of the difference. Houses with the lowest energy efficiency feature an average difference ranging from -15% to -56% of the relevant EPC. Conversely, the most efficient houses display higher-than-theoretical energy use, with average differences ranging from 39% to 54% of the relevant EPC. These results highlight the potential for occupant behaviour to undermine the effectiveness of policies that expect a theoretical EPC to translate to real savings in energy use.

Chapter 3: Evaluating a national residential energy efficiency subsidy scheme using whole-home energy use data

One of the most popular policy tools used to improve energy efficiency in buildings is a subsidy towards the upgrade of certain dwelling measures (retrofit). Subsidies targeted towards the residential sector are warranted since the residential sector represents 25.4% of final energy use in the EU in 2016 (Eurostat 2019a). They are also justified by the fact that 75% of EU buildings are energy inefficient and that only 0.4-1.2% of the building stock is renovated annually among EU member states (European Commission 2018). Policymakers rely on retrofit to increase energy efficiency and lower emissions from existing dwellings. However, the empirical evidence on the effectiveness of retrofit is mixed (Alberini and Towe 2015; Allcott et al. 2015; Allcott and Greenstone 2012).

This chapter evaluates the impact of a national retrofit scheme, using a unique dataset of whole-home energy use with subsidy details for a sample of natural gas-heated homes (n=7,832 households) over a two-year period. This study measures the extent to which domestic retrofit delivers on the promise of real energy use savings. The study focuses on Ireland, a country which has been a poor performer in decarbonising residential energy use.

This study makes several important contributions. It is one of the largest studies of retrofit using whole-home energy data for a general housing sample, who do not disproportionately experience fuel poverty (Fowlie et al. 2018). Secondly, it uses whole-home energy data to capture potential spill overs between fuel sources induced by retrofit. This is not captured in other papers examining retrofit effectiveness (Coyne et al. 2018; Scheer et al. 2013). Finally, this study addresses concerns regarding self-selection issues associated with the decision to undergo a retrofit. Most studies of retrofit compare a treatment group that receives a subsidy and a control group that do not (Fowlie et al. 2018; Scheer et al. 2013).

In the absence of experimental variation, this study considers two control groups: homes that never receive a retrofit (consistent with prior literature) and a second control group of homes that received a retrofit prior to the observation period. This helps account for potential self-selection issues related to the choice to undergo a retrofit.

Results indicate that retrofits reduce energy use by 943 kWh/year, on average. However, the magnitude of savings depends on the combination of measures installed. Additionally, actual energy use is 23% lower than the EPC-suggested level. Within this, more efficient homes consume more energy than expected. Finally, evidence suggests that retrofits offer better value for money when measured by actual changes in energy use, instead of theoretical changes in the EPC.

These results present promising findings on the effectiveness of retrofit, but highlight possible unintended consequences of the policy, where households avail of the subsidy and consume more energy post-retrofit. Although this is likely one of the expected outcomes of such a retrofit policy, it hinders progress towards national energy efficiency targets.

Chapter 4: A Model of Technology Diffusion to Forecast Data Centre Electricity Use

This chapter studies the scope for energy efficiency in one of the fastest growing industrial energy end-users: data centres. Data centres are a critical component of the modern economy, facilitating cloud computing and communication. In 2015, data centres in the EU were estimated to consume 78 TWh of electricity per year, 2.5% of total electricity use (European Commission, 2015). In 2018, data centres are estimated to be responsible for one per cent of global electricity use (Masanet et al., 2020). The uncertain yet increasing presence of data centres poses a challenge for national generation and transmission network planning.

Although technological advances are expected to improve data centre energy efficiency (IEA, 2017), the specific technology and pattern of adoption are unknown. This uncertainty is a significant concern for policymakers attempting to guide national energy and use and emissions towards EU-level 2030 targets (European Commission 2018).

This paper applies an epidemic model of technology diffusion to forecast how potential efficiencies in data centre energy use could be adopted over time. It is motivated in large part by the rapid rise in data centre energy use. The method applied in this paper can be applied to any existing or emerging energy efficiency technology, using limited information. The specific innovation considered in this study is a switch to direct liquid server cooling, which addresses a number of challenges by rising server power density.

Liquid cooling has a higher thermal carrying capacity than air, can be retrofitted to existing units and can reduce the required floor space (Sickinger et al. 2014). Liquid cooling could also help data centres provide low-carbon waste heat supply (Ebrahimi et al. 2014).

This is the first paper to use an epidemic model of technology diffusion in the context of the data centre sector and it serves as a helpful resource for researchers that are dealing with the need to provide sectoral forecasts under uncertainty with little detailed information. It considers the adoption of liquid server cooling in Ireland, a country that is responsible for 14% of the global trade in ICT services (OECD, 2017) and where data centres are forecast to consume between 28% and 37% of national electricity demand by 2028 (EirGrid, 2019).

Results suggest that technology adoption could lower national electricity demand by between 0.81% to 3.16%, depending on whether the technology could be adopted by existing facilities. The methods used here serve as a technology-agnostic resource for researchers that need to perform forecasts under uncertainty with limited information.

Chapter 5: The benefit of energy systems integration: The Irish data centre sector and electro-thermal energy storage solutions.

This chapter is motivated by a commonly observed issue where an energy efficiency technology that benefits different stakeholders fails to be adopted. It connects two distinct strands of literature on i) the Energy Efficiency Gap, which theorizes there is a relative social under-adoption of energy efficient technologies (Jaffe and Stavins 1994a) and ii) the lack of collaboration between public and private stakeholders, where different discount rates result in a lack of investment (Solow (1963); Arrow & Lind (1978)).

Binding EU 2030 targets for renewable generation, emissions reduction and energy efficiency (European Commission, 2019) pose a particular challenge for Ireland, which features a large share of intermittent renewable generation, limited record of low carbon heating and an expected surge in data centre energy use, which are forecast to drive three quarters of the growth in national electricity demand from 2017-2026 (Oireachtas 2017).

This is the first study to evaluate the national economic benefit of an energy efficiency technology that fosters energy systems integration. It connects two distinct strands of literature on small-scale data centre energy efficiency and large-scale consequences of data centres on power systems. It considers a commercially available large-scale technology that uses a charging cycle to convert electricity into hot and cold thermal energy. It also stores electricity, facilitates increased RES generation and helps improve system demand response.

Results model a representative data centre paired with technical parameters of the energy efficiency technology using a forecast of Irish data centre construction. Indirect benefits estimate the hot water available for use in another sector due to technology adoption. Tertiary benefits are quantified using ENGINE, a power systems model of the Irish economy (D. Z. Fitiwi et al. 2020). Results suggest that adoption could lower sectoral energy use by 26% and supply 12.40 TWh of hot water for a 4th Generation district heating network over the 2019-2028 period. A 2030 power systems analysis suggests that adoption reduces renewable electricity capacity requirements by 6.92% and lowers system-wide emissions by 3%.

Results highlight the potential for technology adoption to deliver benefits in multiple sectors. Although results are specific to Ireland and the EET considered, it represents an important example of the potential for sector coupling to help achieve climate targets. It also provides a methodology that can be applied to other technologies, industries and power systems.

Chapter 6: Conclusions

Chapter 6 presents concluding remarks from the previous chapter, including a discussion of key policy implications. It also features a discussion of limitations or this research and outline some of the possible areas for further research.

Chapter 2: Testing the accuracy of residential Energy Performance Certificates

2.1 Introduction

2.1.1 Residential energy policies

Approximately 75% of buildings do not meet energy efficient standards as defined by the EU building standards (European Commission 2019b). This is likely because 35% of the EU dwelling stock is over fifty years old (BPIE 2011) and only 0.4-1.2% of the building stock is renovated annually, depending on the member country (European Commission 2019b). The residential sector represented 25.4% of final energy use in the EU in 2016, with the majority of energy (79.2%) used for space and water heating (Eurostat 2019a).

The EU has set targets for renewable generation, emissions reduction and energy efficiency to achieve climate neutrality by 2050 (European Commission 2019a). 2030 climate targets include i) sourcing 32% of the energy mix from renewable sources, ii) reducing GHG emissions by 40% from 1990 levels and iii) a 32.5% improvement in energy efficiency, relative to a 2007 forecast (European Parliament 2018). Improving energy efficiency is a key way to reduce emissions, representing almost 40% of the potential for reducing greenhouse gases for less than €60 per metric tonne of carbon dioxide equivalent (McKinsey 2010).

The EU Energy Performance of Buildings Directive (EPBD) is a regulation that aims to improve building energy efficiency in member states (European Commission 2019b). It emphasises the use of Energy Performance Certificates (EPCs) for building sales and rentals (European Commission 2018) to improve information for buyers and sellers on the indicative energy performance of a building. EPCs also contributes towards other aspects of the EPBD, such as providing guidance on possible energy efficiency improvements[1]. In Ireland, the Climate Action Plan plans to reduce energy use in buildings through a policy to upgrade 500,000 homes to an energy efficient B2 standard (Government of Ireland 2019). This is equivalent to a quarter of the national dwelling stock (Central Statistics Office 2017).

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[1] See https://ec.europa.eu/energy/en/content/introduction-11

2.1.2 The value of Energy Performance Certificates

Despite policymaker enthusiasm for introducing EPCs, evidence on the relationship between EPCs and property prices is mixed. Although studies for the EU and Ireland found correlations between a better rating and a higher sales or rental prices in EU countries (European Commission 2013; Hyland et al. 2013), German homeowners found it was difficult to translate EPCs into the value of energy efficiency and did not consider it a priority in their property purchase decision (Amecke 2012). Evidence from Northern Ireland that applies quantile regression finds evidence of a premium attached to energy efficient dwellings at high sales prices and discounts attached to low energy efficiency dwellings for sale at high prices (McCord et al. 2020).

EPCs have also been related to other important outcomes. Comerford et al. (2018) find that introducing an EPC induced investment in household energy efficiency in the UK. Evidence from Wales suggests a statistically significant price premium of 12.8% for A/B-rated dwellings (Fuerst et al. 2016). However, the authors make an important observation that energy performance may not be the only factor driving this price premium, as it is likely to be correlated with other desirable factors.

2.1.3 The limitations of Energy Performance Certificates

The mixed evidence on the value of EPCs is unsurprising. Evidence for the Irish EPC suggests that trust in the measure could be undermined due to systematic bunching[2] in the distribution of EPCs with regard to property sale prices (Hyland et al. 2016). Furthermore, EPCs have been shown to suffer from a lack of ex-post verification between measured and theoretical energy use (Burman et al. 2014; van Dronkelaar et al. 2016). There is often a disparity between the engineering model-based EPC and actual energy use (Cozza et al. 2020; De Wilde 2014; Gram-Hanssen and Georg 2018; Majcen et al. 2013; Zou et al. 2018). This is known commonly as the Energy Performance Gap (EPG)[3].

[2] Bunching is defined by Hyland et al. (2016) as “an excess frequency of homes on the favourable side of a threshold accompanied by a much-reduced frequency on the unfavourable side of that threshold.”
[3] The Energy Performance Gap can be considered within the broader theory of the Energy Efficiency Gap (Jaffe and Stavins 1994a) which considers the under-adoption of energy efficient goods with a positive net present value at the societal level.

Research has found a negative relationship between dwelling energy efficiency and the direction of the EPG, with a positive EPG for energy efficient dwellings and a negative EPG for the least efficient (Cozza et al. 2020; Majcen et al. 2013; van den Brom et al. 2018). Studies of the EPG have identified the influential role of occupant behaviour (De Wilde 2014; Gram-Hanssen and Georg 2018; Zou et al. 2018).

There has been substantial evidence on the behavioural factors influencing energy use when dwelling energy efficiency changes (‘retrofit’). Many studies have identified ‘rebound’ effects, where a lower effective price of heating encourages increased energy use (Heesen and Madlener 2018; Sorrell et al. 2009). Some studies of retrofit have found a ‘prebound’ effect, where the least energy efficient dwellings consume less heating than expected (per their EPC) following a retrofit (Sunikka-blank and Galvin 2012). Accurate estimates of the EPG are complicated by improvements in dwelling energy efficiency that may induce any behavioural change in the occupant. Aydin et al. (2017) show a negative relationship between household income and rebound in gas use[4]. Research into an Irish energy retrofit also found that socially vulnerable occupants often under-heat their homes, use more energy and alternative heating fuels following a retrofit (Coyne et al. 2018).

The rapid nature of technological change also poses challenges for research into the EPG. Delghust et al. (2015) note how research needs to study all fuels used in the house, including electricity, which represents a greater share of energy use in efficient dwellings and is becoming more popular due to changes in heating systems.

2.1.4 Contribution

Evidence into the EPG suggests that policies aiming to reach a certain EPC standard may not deliver the expected energy savings (Cozza et al. 2020; Gram-Hanssen and Georg 2018; Zou et al. 2018). Research has noted that country-level differences in the implementation of the EPBD require country-specific studies of the Energy Performance Gap (Andaloro et al. 2010; Delghust et al. 2015). This is especially true for Ireland, where there are ambitious plans to upgrade the energy efficiency of the dwelling stock (Government of Ireland 2019).

[4] Studies of domestic energy use are complicated by such ‘rebound’ effects, where improvements in energy efficiency lower the cost of energy services, thus increasing energy use (Sorrell et al. 2009)

This is the first paper that tests for the presence of an EPG using a measure of whole-home energy use for a non-social housing sample of 9,923 households that do not receive a retrofit. The key contribution of this paper is the combination of i) the analysis of whole-home energy use, ii) for a non-social housing sample that iii) does not feature behavioural changes that would be induced by retrofit. Previous studies have considered one or two of these aspects, but this is the first study combines all three to overcome limitations of previous studies.

Firstly, this estimate of the EPG considers a whole-home measure of energy use. This is different to other studies which focus exclusively on the EPG for a single fuel source for space and water heating (Cozza et al. 2020; van den Brom et al. 2018). The benefit of considering both electricity and gas demand, is that it can capture fuel switching behaviour amongst these fuel sources. This is an important contribution due to the increasing use of alternative fuels in households, especially for socially vulnerable homes in low-efficiency dwellings (Coyne et al. 2018; van den Brom et al. 2018). Accounting for electricity use is relevant as energy efficient dwellings tend to have a higher share of electric heating (Delghust et al. 2015). This paper uses a comprehensive dataset that eliminates complications from fuel-switching which may overstate the true EPG when measured using only one fuel source (Cozza et al. 2020; van den Brom et al. 2018).

Secondly, this research features a generally representative sample of households over a two-year period. Some other EPG studies only feature social housing tenants (Majcen et al. 2013; van den Brom et al. 2018), a cohort which has been shown elsewhere to have particular energy use behaviour (Coyne et al. 2018; Delghust et al. 2015). For this reason, a general sample of households may provide a more general view of the EPG.

Thirdly, our estimate of the EPG does not include changes in occupant behaviour that would be induced due to a change in dwelling energy efficiency from a retrofit. Other prominent EPG studies note the potential for retrofit in their sample (Cozza et al. 2020; Heesen and Madlener 2018). However, research has shown that a retrofit can induce a behavioural change in occupant energy use (Sorrell et al. 2009; Sunikka-blank and Galvin 2012; Webber et al. 2015).

The chapter is laid out as follows: Section 2.2 details select relevant literature and background on the Irish context. Section 2.3 details the model of real and actual energy use. Section 2.4 details the data and variables used. Section 2.5 presents results, while Section 2.6 discusses the main findings. Section 2.7 concludes with some policy recommendations.

2.2 Literature

This section details how consumer behaviour is hard to measure within the context of modelling building energy use. It then provides background to the Irish market, the setting of this study. Finally, the Irish EPC and some of its key assumptions are noted.

2.2.1 Studies of the Energy Performance Gap

The Energy Performance Gap (EPG) is central to this study. As noted in Section 2.1.3, there are a diverse range of studies of the difference between actual energy use and the level calculated by an EPC. Differences between the engineering model-based EPC and actual energy use often arise (Cozza et al. 2020; De Wilde 2014; Gram-Hanssen and Georg 2018; Majcen et al. 2013). The different implementations of the EPBD across member states justifies the need for country-specific research (Andaloro et al. 2010; Delghust et al. 2015). The EPG often has a distributional aspect, where low energy efficiency households and socially vulnerable occupants demonstrate substantial under-consumption, relative to the EPC (Cozza et al. 2020). Studies of the EPG for a sample of social housing tenants found that energy-efficient dwellings use more energy than calculated and vice versa (Majcen et al. 2013; van den Brom et al. 2018).

Studies of the EPG are complicated by behavioural changes in the occupant (‘rebound’) observed due to retrofit, where a lower effective price of heating encourages increased energy use (Heesen and Madlener 2018; Sorrell et al. 2009). In some cases, a retrofit has been shown to lead to a fall in energy use (Sunikka-blank and Galvin 2012). Aydin et al. (2017) highlight a negative relationship between household income and rebound in gas use, with the lowest income quintile featuring an average rebound almost ten percentage points higher than the average rebound for the rest of the distribution.

Estimates of the EPG are further complicated if improvements in building energy efficiency from a retrofit do not deliver the expected improvement (Gram-Hanssen and Georg 2018). In the UK, Dowson et al. (2012) note that model predicted energy savings may be halved in reality due to poor installation, monitoring and increased heating use post-retrofit. Research into an Irish energy retrofit also found that socially vulnerable occupants often under-heat their homes, and use alternative heating fuels (Coyne et al. 2018).

Many studies of the EPG find occupant behaviour to be an important factor (De Wilde 2014; Gram-Hanssen and Georg 2018; Zou et al. 2018). In a commercial context, actual energy use could be 2.5 times larger than predicted (Menezes et al. 2012). Herrando et al. (2016) find an average EPG of 30%. Majcen et al. (2013) find that energy inefficient homes consume less than predicted and energy efficient homes consume more than predicted for a sample of 200,000 social housing tenants in the Netherlands. Van den Brom et al. (2018) find similar results for a larger sample of Dutch social housing tenants.

Most studies only consider energy for space and water heating, and do not account for fuel switching, which has been shown for select cohorts (Coyne et al. 2018; Delghust et al. 2015). Although research has identified discrepancies between the actual and theoretical level of energy use, this message has not reached policymakers (Gram-Hanssen and Georg 2018). Reasons for this discrepancy include the limitations of building modelling, inaccurate assumptions regarding occupant behaviour and flaws during the building design phase.

In summary, research has shown that modelling residential energy use is challenging. Part of this challenge arises from how consumer behaviour changes over time through rebound effects from changes in building energy efficiency. The EPG has also been shown to be particularly sensitive to the socioeconomic status of occupants. For these reasons, a study of the EPG using a measure of whole-home energy use for a general sample of households that did not receive a retrofit is highly relevant.

2.2.2 Ireland as a case study

Ireland intends to improve energy efficiency (lowering energy use) by 20% before 2020, relative to average national energy use from the period 2001-2005. This equates to savings of 31,925 GWh (DCENR 2009). As part of the EU Energy Efficiency Directive, member states must submit a National Energy Efficiency Action Plan with specific measures designed to improve energy efficiency (European Union 2012). By early 2017 Ireland only achieved a 12% improvement and is expected to miss the 2020 target by 3.77% (DCCAE 2017a). Achieving compliance for the 2020 target could cost €80-140 million[5].

Despite this, Ireland has made progress in improving residential energy efficiency. Energy use per dwelling has fallen by 32% from 1990-2015 due to technology improvement, retrofits, building regulations and macroeconomic factors (SEAI 2016). However, there is more to be done as Ireland has the fourth highest level of greenhouse gas emissions in the EU of 13.3 tonnes of CO_2 equivalent per capita in 2017 (Eurostat 2020). Irish homes consume the most energy on average in the EU, with the second largest average occupancy in the EU-28 of 2.7 persons per house (SEAI 2018). According to EU-SILC data from 2017, 8.3 per cent of the Irish population live in apartments (Eurostat 2019b), lower than the EU average of 41.9 per cent and almost half the second-lowest country, the UK (14.7 per cent). Electricity plays an important role in residential energy use. In 2017, over 20 per cent of electricity used in the Irish residential sector was for space and water heating[6].

Irish interventions to improve residential energy efficiency aim to simplify consumer decision-making for durable appliances (Carroll et al. 2016), to improve dwelling energy efficiency through a grant-supported retrofit (Scheer et al. 2013) or to alter intraday electricity (Di Cosmo et al. 2014) and gas (Harold et al. 2018) usage patterns. Research has established how information from an EPC on theoretical dwelling energy efficiency is positively associated with property sale and rental prices (Hyland et al. 2013). Hyland et al. (2016) suggest there is scope to improve the Irish EPC due to systematic bunching in the distribution of ratings.

[5] See https://www.rte.ie/eile/brainstorm/2017/1124/922516-missing-climate-and-energy-targets-will-cost-ireland-millions/

[6] See https://www.seai.ie/data-and-insights/seai-statistics/key-statistics/residential/#:~:text=For%202018%20we%20estimate%20that,%2C%20and%202%25%20for%20cooking.

Evidence of an EPG presents an issue if policymakers expect real emissions reductions from improving the dwelling stock to a certain EPC threshold. In Ireland, the government aims to retrofit 500,000 homes to B2 EPC standard by 2030 (Government of Ireland 2019). The presence of an EPG would cause actual savings to deviate from the level expected.

2.3 Methodology and Data

2.3.1 Methodology

Policymakers attempting to reduce emissions by upgrading the dwelling stock to a certain EPC standard face a problem if an EPC is based on assumptions regarding theoretical occupant energy use (TQ_i) that does not accurately reflect actual occupant energy use (AQ_{it}). Consequently, the presence of an Energy Performance Gap (EPG) may limit the effectiveness of policies designed to lower residential energy use by targeting a benchmark EPC standard. This paper features three distinct research questions that explore the existence of an EPG and the factors influencing actual energy use. Each research question directly corresponds to a subsection of the results.

The first research question (Section 2.4.1) tests for the presence of an Energy Performance Gap with a null hypothesis that the EPC accurately reflects actual occupant usage (Equation 2.1). For a given household *i* in year *t*, actual household energy use (AQ_{it}) is equal to the theoretical EPC level of energy use (TQ_i) if there is no Energy Performance Gap. Since an EPC estimate does not account for appliance use and occupant behaviour, it will not reflect true dwelling energy use (Section 2.3.4). It is expected that this difference will not be equal to zero (Cozza et al. 2020; van den Brom et al. 2018; Zou et al. 2018). This result is presented in aggregate (kWh/year) and as a percentage of the EPC (Cozza et al. 2020).

$$\mathrm{H0{:}\ AQ_{it} - TQ_i = 0} \qquad [2.1]$$

This question is highly relevant since the Energy Performance Gap is widely accepted in the research community but often ignored in policy discourse (Gram-Hanssen and Georg 2018). This is the first study that controls for whole home energy use, the sample and the potential for retrofit-induced behavioural changes.

The second research question (Section 2.4.2) aims to quantify the extent to which key dwelling factors influence actual energy use at the bimonthly level (n=149,518 readings). It uses a linear regression at the bimonthly time frequency and accounts for the influential role of seasonality in energy use. It considers the EPC and relevant dwelling characteristics (detailed in Section 2.3.3 and 2.3.5, respectively). It models actual energy use (AQ_{it}) for household *i* in period *t* as a function of the theoretical energy efficiency of the dwelling (TQ_i), a vector (X_i) of key dwelling features such as dwelling type, size, number of stories, age and a vector (W_t) of time-varying weather controls (Equation 2.2). Results (Section 2.4.2) begin by regressing actual energy use on the fully interacted EPC (Model 1), then expands to include dwelling characteristics (Model 2) and a time fixed effect (Model 3).

$$\mathrm{AQ_{it}} = \mathrm{a_i} + \beta_1 \mathrm{TQ_i} + \beta_2 \mathrm{X_i} + \beta_3 \mathrm{W_t} + \mathrm{u_{it}} \qquad [2.2]$$

The third research question (Section 2.4.3) explores whether the relationship between actual energy use and key dwelling factors persists across each of the five EPC bands *j* (Equation 2.3). This is motivated by the potentially different influence of covariates across the EPC spectrum. This relationship is explored for each specific EPC grade at the bimonthly frequency (Model 4) using the linear regression in Model 3, featuring a time fixed effect.

$$\mathrm{AQ_{ijt}} = \mathrm{a_i} + \beta_1 \mathrm{TQ_{ij}} + \beta_2 \mathrm{X_i} + \beta_3 \mathrm{W_t} + \mathrm{u_{it}} \qquad [2.3]$$

2.3.2 Data sources

Household energy use data of electricity and natural gas (A) is sourced from Electric Ireland, the largest residential electricity utility in Ireland. This paper studies homes with natural gas heating observable by meter readings. This data is observed from November 2014 to June 2017, sixteen bimonthly[7] periods. This is merged with dwelling information from SEAI (B) using the common meter point number. Time-varying weather (C) controls are also included (Table 2.1). The sample consists of 9,923 homes, 19,251 customer-year observations and 149,518 bimonthly readings. Appendix A2 details the data cleaning process, including the removal of 333 households with highly abnormal energy use. This did not affect later results. As in Cozza et al. (2020), such households likely represent a holiday home that is sparingly used. The sample distinguishes between households that never receive a retrofit (n=8,311) and households that receive one prior to the observation period (n=1,612 houses)[8].

Table 2.1: Data sources

ID	Data	Details	Source
A	Energy use	Electricity and gas readings	Electric Ireland
B	Building Energy Rating	Dwelling features, EPC	SEAI
C	Weather	Heating Degree Days (HDDs), Rainfall	Met Eireann

Note: Appendix 2.C details the data cleaning process and the handling of outliers and unreliable data.

2.3.3 The Irish EPC

The Sustainable Energy Authority Ireland (SEAI) promotes energy efficiency and operates the Building Energy Rating (BER) scheme, which is the Irish EPC. A BER is required for every property sold, rented or in receipt of a grant-supported retrofit (European Union 2002). The BER denotes the theoretical energy performance of a dwelling using a 15-point scale from A1-G in units of kilowatt-hour per metre squared per annum (Table 2.2). It is compliant with the EU Energy Performance of Buildings Directive and is based on both IS EN 13790 and the UK Standard Assessment Procedure for dwelling energy ratings (SEAI 2012).

[7] The term ‘bimonthly’ denotes a period of two months. This is not to be confused with the ‘twice-monthly’ frequency.
[8] Appendix 2.F performs a robustness check of annual results, split by subsample and finds no major differences.

Table 2.2: Building Energy Rating (BER) levels and Simplified EPC

BER	**A1**	**A2**	**A3**	**B1**	**B2**	**B3**	**C1**	**C2**	**C3**	**D1**	**D2**	**E1**	**E2**	**F**	**G**
	<25	>25	>50	>75	>100	>125	>150	>175	>200	>225	>260	>300	>340	>380	>450
Simple	**AB**						**C**			**D**		**E**		**FG**	
EPC	0-150						151-224			225-299		300-379		>380	

Source: SEAI. Note: Values in kWh/m^2/year. Simplified EPC is used in later analysis for convenience.

$$TQ_{Total} = Q_{SpaceHeat} + Q_{WaterHeat} + Q_{AuxEnergy}\,Q_{Lighting} - Q_{PV} - Q_{CoGen} \qquad [2.4]$$

The BER calculates “the energy required for space heating, ventilation, water heating and lighting, less savings from energy generation technologies” (SEAI 2012). Equation 2.4 details its components, which are similar to other dwelling asset rating models (Majcen et al. 2013; van den Brom et al. 2018). The BER is influenced by factors such as dwelling size, type, insulation, ventilation and heating system (SEAI 2014). It reflects theoretical primary energy use for space and water heating, ventilation and lighting[9]. It does not include energy consumed by appliances, estimates to be roughly 20% of domestic energy use (SEAI 2018). There is no formal validation of the BER awarded from the in-home audit using real billing information. This deficiency has also been noted in studies of the UK EPC (Burman et al. 2014; van Dronkelaar et al. 2016). Collins & Curtis (2018) examine changes in BER pre- and post-retrofit and find discontinuities in the national distribution of post-retrofit BERs, but not in the pre-retrofit BERs. They find no evidence of illicit behaviour by BER assessors, but a high rate of low energy lighting prevalent in the distribution. This study is the first evaluation of the BER using actual energy use data for a sample without retrofit.

Weather conditions are considered at a local level but the model assumptions regarding occupant heating behaviour are more important (SEAI 2012). The BER assumes that the heating season runs from October to May inclusive, with the primary living space being heated to 21 degrees Celsius and the rest of the house heated to 18 degrees Celsius for eight hours a day (SEAI 2012). Given that space and water heating demand is the single largest energy demand in the home, the *a priori* expectation is that differences between actual and theoretical energy use would be largely driven by deviations in actual heating behaviour, especially after accounting for appliance usage, which is not included in the EPC.

[9] Primary energy use includes energy delivered to the home and an overhead for energy lost in generation and transmission.

2.3.4 Dependent variable: Actual energy use

Most studies of the Energy Performance Gap draw a comparison between metered energy for heating with the theoretical EPC (Cozza et al. 2020; Heesen and Madlener 2018; Majcen et al. 2013; Scheer et al. 2013). Such studies fail to capture electricity used as a secondary fuel (nor do they seek to). This omission has the potential to overstate the true Energy Performance Gap and may acutely affect the most energy efficient homes, which feature a larger share of electricity use (Delghust et al. 2015). It may also disproportionately affect homes that engage in substantial fuel switching, such as low income social housing occupants (Coyne et al. 2018). For these reasons, we include an adjustment for appliance use to allow comparability with the EPC (since the EPC does not include appliances).

This study leverages the rich data available to develop a measure of the Energy Performance Gap that compares whole-home energy use (natural gas plus electricity) with the theoretical Irish EPC, which is denoted in units of primary energy use. Table 2.3 summarises the primary energy factors for the sample with an average ratio of 1.24, leading to actual meter readings being inflated for comparison with the EPC. Any mention of energy from this point is referring to primary energy use, unless explicitly stated otherwise. While it would be interesting to separate primary energy consumption into electricity and gas, the EPC is an aggregate measure which does not distinguish separate consumption levels.

In order to compare theoretical energy use from the EPC, the variable of actual energy use is adjusted to account for the heatable floor space and the ratio of primary to delivered energy (Equation 2.5)[10]. Actual energy use must also be adjusted to reflect the fact that EPCs do not include energy use for appliances within the home. SEAI (2018) estimates that appliance usage comprises, on average, 20% of Irish home energy use. Results in this paper consider two versions of appliance usage (AA_j). The first ($AA_{Relative}$) involves a relative scaling of usage to a factor of 0.8, based on SEAI (2018).

$$AQ_{it} = \frac{DeliveredEnergy_i}{HeatableFloorArea_i} * \frac{PrimaryEnergy_i}{DeliveredEnergy_i} * AA_j \qquad [2.4]$$

[10] Appendix A1 provides more detail on the construction of the dependent variable.

Table 2.3: Summary of household-level primary energy factors

	N	Mean	Median	SD	Min	Max	Skew.	Kurt.
Primary energy	9,923	22674	20165.91	11343.98	-28236.7	122777.9	1.67	8.06
Delivered energy	9,923	18505	16459.11	9431.09	-27848.8	73646.2	1.53	6.89
Ratio (P/D)	9,923	1.24	1.21	0.14	1	3.11	7.31	69.4

Source: Author's calculations using SEAI data (9,923 households). Note: Values in kWh/year. Delivered energy includes energy assumed to be consumed in the dwelling. Primary energy includes generation and transmission losses. The ratio helps to scale metered energy use to reflect actual energy use.

The second version of appliance adjustment accounts for concerns about the distributional effect of a relative appliance adjustment across the spectrum of building energy efficiency. The second appliance adjustment ($AA_{Absolute}$) involves an absolute deduction for annual appliance usage (1,357 kWh/year) for a subset of appliances assumed common to each home (Owen and Foreman. 2012)[11]. The bimonthly panel of 9,923 households (n=149,518 readings) has a completeness of 94.17%, with an average of 15.06 periods present and an average gap of 1.31 periods. Figure 2.1 shows the seasonal pattern of sample energy use.

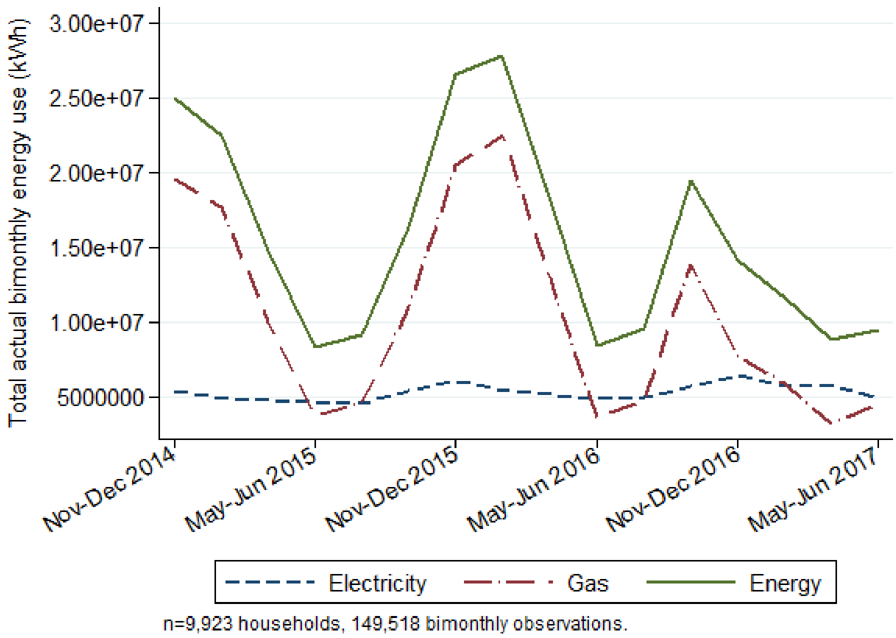


Figure 2.1: Total bimonthly actual energy use over time ($AA_{Relative}$)

[11] This is detailed further in Appendix 2.B.

The sample features 9,923 households with one full year of actual energy use ($\mathrm{AQ}_{\mathrm{Y1}}$) and 9,328 observations with an additional second full year ($\mathrm{AQ}_{\mathrm{Y2}}$). Table 2.4 compares mean annual actual ($\mathrm{AQ}_{\mathrm{Y1}}$, $\mathrm{AQ}_{\mathrm{Y2}}$) and theoretical ($TQ$) energy use, with all variables in units of annual energy use per square metre. Figure 2.2 compares the distributions of annual actual ($\mathrm{AQ}_{\mathrm{Y1}}$, $\mathrm{AQ}_{\mathrm{Y2}}$) and annual theoretical energy use (TQ). It shows a higher share of observations in the A- and B-rated (most efficient) range of the distribution and a lower share of observations in the C- and D-rated range of theoretical energy efficiency. The presence of large positive actual energy use in the right tail of the distribution is notable, especially since the EPC lacks an upper bound on theoretical energy efficiency for G-rated homes. A Z-test is performed for each combination of the three variables that suggests three distributions are similar, with $Z_{\mathrm{AQ}_{\mathrm{Y1}},\mathrm{AQ}_{\mathrm{Y2}}} = 0.76$, $Z_{\mathrm{AQ}_{\mathrm{Y1}},TQ} = 0.24$ and $Z_{\mathrm{AQ}_{\mathrm{Y2}},TQ} = 0.15$.

Table 2.4: Comparison of mean annual actual and theoretical energy use ($\mathbf{AA_{Relative}}$)

	N	Mean	SD	Min	Max	Skew.	Kurt.
Actual energy use ($\mathrm{AQ}_{\mathrm{Y1}}$)	9,923	197.80	124.26	9.51	1,777.77	1.50	10.80
Actual energy use ($\mathrm{AQ}_{\mathrm{Y2}}$)	9,328	211.16	123.73	11.29	1,687.24	1.35	8.55
Theoretical energy use (TQ)	**9,923**	**235.44**	**101.03**	**39.97**	**1,240.73**	**1.95**	**11.3**

Note: Values in kWh/m²/year.

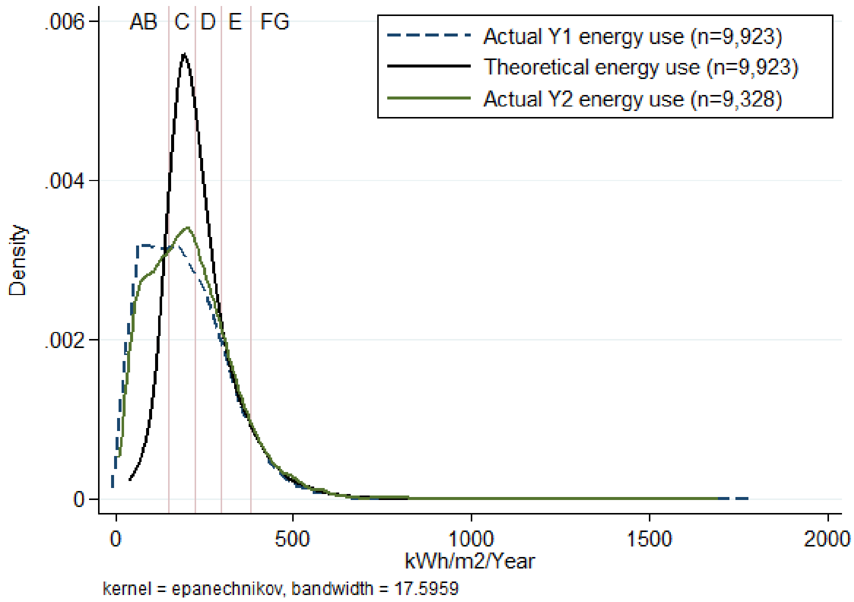


Figure 2.2: Distribution of theoretical and actual annual energy use ($\mathbf{AA_{Relative}}$)

2.3.5 Dwelling characteristics and weather

The SEAI dataset features dwelling information on house type, age, height and heatable floor area. Importantly, it includes a variable of theoretical energy use in units of kWh/m^2/year, which informs the categorical EPC. Table 2.5 summarises key continuous variables for the sample used in later bimonthly analysis that measures the factors associated with actual energy use (Section 2.4.2, 2.4.3). Research has identified correlations between weather and electricity (Kavousian et al. 2013), heating (Quayle and Diaz 1979) and appliance use (Hart and De Dear 2004). To account for this, households are linked at the county level with the nearest weather station[12]. A Heating Degree Day variable reflects the number of days the daily mean temperature is below 15.5 degrees Celsius. A total bimonthly rainfall variable also features. This reflects days where occupants are more likely to require heating. A total bimonthly rainfall variable also features.

Table 2.5: Summary of continuous dwelling and weather control variables

Variable	Mean	SD	Min	Max
Number of floors	1.94	0.48	0	4
Year of Construction	1979	28.98	1753	2017
Percentage of home that is living area	21.33	9.81	0	81.1
Bimonthly heating degree days	53.29	10.6	10	61
Total bimonthly precipitation (in cm)	18.78	104	5.63	55.6

Note: n=9,923 homes. Note: Weather for 16 bimonthly periods and five weather stations.

Table 2.6 compares key theoretical energy efficiency for the sample and the population of SEAI EPC records (reflecting roughly half of the national dwelling stock)[13]. An additional comparison by dwelling type includes the 2016 census national occupied dwelling stock, which does not feature EPC information. SEAI data underrepresents detached dwellings, overrepresents apartments and terrace homes. This is because an EPC is only required when a property is sold, leased or undergoes a retrofit. Compared to the SEAI population, the sample has a higher share of C houses and a similar share of AB and D houses. The sample under-represents detached homes and apartments and over-represents semi-detached and terraced. It is important to consider the potential for the sample to understate effects for FG-rated homes and to over-emphasise results for C-rated homes nationally.

[12] Available on the European Climate Assessment & Dataset http://eca.knmi.nl/dailydata/customquery.php
[13] Appendix 2.B compares dwelling type and theoretical energy efficiency for the initial and analysis sample.

Table 2.6: Sample v SEAI population dwelling comparison

		Sample (n=9,923)		SEAI Population (n=729,599)		Occupied Dwelling Stock (n=1,675,795)*	
		Count	**%**	**Count**	**%**	**Count**	**%**
EPC	AB	1,351	13.61	104,084	14		
	C	4,257	42.90	270,628	37		
	D	2,486	25.05	178,172	24		
	E	1,059	10.67	86,401	12		
	FG	770	7.76	90,324	12		
Dwelling Type	Detached	1,197	12.06	232,677	32	715,133	43
	Apartment	873	8.80	144,289	20	204,145	12
	Semi-detached	3,565	35.93	193,543	27	471,948	28
	Terrace	4,288	43.21	159,100	22	284,569	17
	Total	**9,923**	**100**	**729,599**	**100**	**1,675,795**	**100**

Note: 2016 census values sourced from the Irish CSO for occupied households.

2.4 Results

As noted in Section 2.3.1, results are presented in order of the three research questions. Section 2.4.1 quantifies the Energy Performance Gap by testing for significant differences in annual values of actual and theoretical energy use. Section 2.4.2 features regressions using the bimonthly data account for relevant covariates. Finally, Section 2.4.3 studies potential heterogenous effects by EPC category. Section 2.3.4 introduced two variants of actual energy use to account for appliance use. In each subsection, the first set of results features the dependent variable constructed using the RELATIVE appliance adjustment (AARelative). The second set features the dependent variable constructed using an ABSOLUTE appliance adjustment (AAAbsolute).

2.4.1 Annual results

The sample features 19,251 annual observations of energy use (AQ), representing 9,923 observations of one full year (AQ_{Y1}) and a further 9,328 observations featuring a second full year of energy use (AQ_{Y2})[14]. Energy use variables are in units of kilowatt-hours per year (kWh/year). Table 2.7 performs a test of paired differences shows that average annual actual energy use is significantly lower than the theoretical level from the EPC, suggesting the existence of an Energy Performance Gap (EPG).

[14] Appendix 2E features a robustness check that splits data for each full year of actual energy use (Y1, Y2).

The average deficit in annual consumption is 2,279 kWh, roughly 15% of the average value of 15,000 kWh/year considered by the Irish utilities regulator (CRU 2017)[15]. Differences between the sample and the regulator reference likely stem from differences in the samples. Results denote the difference between Mean AQ and Mean TQ ('Difference') and the percentage difference as a percentage of the Mean TQ ('% Difference'), which is similar to the measure used by Cozza et al. (2020).

Table 2.7: Difference between annual actual and theoretical energy use ($AA_{Relative}$)

		Actual Annual Energy Use (AQ)		Theoretical Annual Energy Use (TQ)		T-Test of Equality of Means			
						Difference		SE	P-Value
	n	Mean AQ	Median AQ	Mean TQ	Median TQ	Mean	%		
$AQ_{All} - TQ$	19,251	10,869	10,167	13,148	11,402	- 2,279	- 17.33	61	0***
EPC Grade									
AB	2,601	10,569	9,661	7,571	6,620	2,998	39.60	122	0***
C	8,269	10,880	10,334	10,826	9,734	54	0.50	70	0.44
D	4,835	10,917	10,231	14,353	12,826	- 3,436	-23.94	104	0***
E	2,051	11,026	10,421	18,133	16,300	- 7,106	-39.19	173	0***
FG	1,495	10,964	9,853	24,962	22,466	- 14,000	-56.09	290	0***
Dwelling									
Apartment	1,674	8,115	7,211	11,595	10,983	- 3,481	-30.02	163	0***
Detached	2,316	13,712	13,150	19,385	17,184	- 5,673	-29.27	247	0***
Semi-detached	6,905	11,398	10,917	14,008	12,495	- 2,610	-18.63	99	0***
Terrace	8,356	10,197	9,712	11,020	9,490	- 823	-7.47	82	0***

***** P<0.01, **P<0.05, *P<0.10. Note: Units in kWh/year. Sample features 9,923 observations of one year of actual energy use and a further 9,328 observations from the same sample of houses with a second year of actual energy use. Medians reported. A test of equality of medians (using signtest STATA command (Snedecor & Cochran, 1989), confirms the same significant differences exist as the T-Test of means (displayed above).**

The most striking observation is a distinct lack of variation in average actual energy use across the entire sample. There is only a difference of 457 kWh/year between the lowest and highest average. This suggests that the demand for energy is unresponsive to the energy efficiency of the dwelling. A similar relationship has been observed in a study of UK office buildings (Better Buildings Partnership 2019). On a comparative basis, there is significant differences between average actual and theoretical energy use. The most efficient homes (AB) feature an average positive difference of 2,998kWh per year, 39% greater than theoretical.

[15] The Irish regulator reference values for average energy use are discussed in Appendix 2D.

Conversely, less efficient homes (D, E, FG) exhibit actual energy use lower than theoretical, with an average difference ranging from 24% for D-rated homes to 56% for F- and G-rated homes. There are also significant differences by dwelling type. Apartments and detached dwellings feature a deficit in the region of 30%. Semi-detached homes semi-detached (19%) and terrace houses (7%) feature a smaller deficit.

Table 2.7 shows a greater-than-theoretical energy use for efficient homes and lower-than-theoretical energy use for less efficient homes, a finding which is consistent with other estimates of the EPG (Cozza et al. 2020; Majcen et al. 2013; van den Brom et al. 2018). However, this result has not previously been shown using a measure of whole-home energy use. In particular, Cozza et al. (2020) find a median EPG of -11% and mean EPG of -6% for a sample of Swiss dwellings. In this study, the median EPG is similar (10.8%), but the mean difference is far greater (-17%).

When using a measure of the dependent variable that features an absolute appliance deduction, results still suggest evidence of an EPG (Table 2.8). The overall average difference is smaller (1,105 kWh, -8.40%), yet larger positive differences are observed for AB-rated homes (53.61%). C-rated homes also consuming more than the theoretical amount (11.20%). FG-rated homes consume less than theoretical (-51.28%), but the magnitude of this difference is smaller. Similar trends are observed across dwelling type.

Results using a measure of the dependent variable that features an absolute appliance deduction still suggests a minor difference 677 kWh/year between the highest and lowest actual energy use averages (Table 8). Within EPC bands, results suggest that an EPG exists, with. The overall average difference is smaller (1,105 kWh, -8.40%), yet larger positive differences are observed for AB-rated homes (53.61%). C-rated homes also consume more than the theoretical amount (11.20%). FG-rated homes consume less than theoretical (-51.28%), but the magnitude of this difference is smaller. A test of equality of medians showing similar significance of results.

Table 2.8: Difference between annual actual and theoretical energy use ($AA_{Absolute}$)

		Actual Annual Energy Use (AQ)		Theoretical Annual Energy Use (TQ)		T-Test of Equality of Means			
						Difference		SE	P-Value
	n	Mean AQ	Median AQ	Mean TQ	Median TQ	Mean	%		
AQ_{All} – TQ	19,251	12,044	11,158	13,148	11,402	-1,105	-8.40	68	0***
EPC Grade									
AB	2,601	11,630	10,499	7,571	6,620	4,059	53.61	147	0***
C	8,269	12,039	11,356	10,826	9,734	1,213	11.20	83	0***
D	4,835	12,119	11,207	14,353	12,826	-2,234	-15.57	120	0***
E	2,051	12,307	11,490	18,133	16,300	-5,826	-32.13	195	0***
FG	1,495	12,187	10,773	24,962	22,466	-12,800	-51.28	308	0***
Dwelling									
Apartment	1,674	8,617	7,507	11,595	10,983	-2,978	-25.68	184	0***
Detached	2,316	15,620	15,003	19,385	17,184	-3,765	-19.42	267	0***
Semi-detached	6,905	12,702	12,063	14,008	12,495	-1,306	-9.32	111	0***
Terrace	8,356	11,195	10,584	11,020	9,490	175	1.59	93	0.06*

***** P<0.01, **P<0.05, *P<0.10. Note: Units in kWh/year. Sample features 9,923 observations of one year of actual energy use and a further 9,328 observations from the same sample of houses with a second year of actual energy use. Medians reported. A test of equality of medians (using signtest STATA command (Snedecor & Cochran, 1989), confirms the same significant differences exist as the T-Test of means (displayed above).**

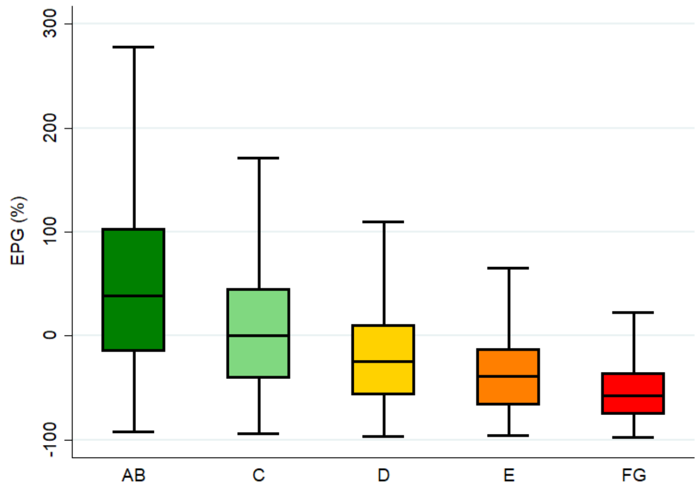


Figure 2.3: Comparison of Energy Performance Gap

Note: EPG presented as the difference between actual and theoretical energy use as a percentage of theoretical energy use. Each box reflects the interquartile range of EPG, with whiskers denoting the adjacent value. Sample includes 19,251 observations. Figure reflects the relative appliance adjustment.

Figure 2.3 illustrates the extent of the EPG across the spectrum of dwelling energy efficiency. It emphasises the substantial differences in the EPG, with a positive EPG for the most efficient dwellings and a negative EPG for the least efficient dwellings.

2.4.2 Bimonthly results

Section 2.4.1 provided evidence of an EPG across the entire EPC spectrum on an annual basis. Sections 2.4.2 and 2.4.3 investigate the factors associated with actual energy use at the bimonthly frequency to better understand seasonal differences (Tables 2.9 - 2.12), using a linear regression (Equation 2.2 and 2.3). There are 149,518 data points in these regressions, indicated in the fourth row from the bottom in each table. In addition to the EPC and dwelling type, each regression controls for the following dwelling characteristics that are related to dwelling energy use, obtained from the EPC: number of floors, year of construction, percentage of home classed as living area (from Section 2.3.5). Regressions also control for weather using a measure of heating degree days and bimonthly rainfall.

Actual bimonthly energy use ($\mathrm{AQ_t}$) is modelled as a function of the bimonthly theoretical energy use ($\mathrm{TQ_t} = \mathrm{TQ}/6$), a full interaction with the categorical EPC, specific dwelling characteristics and weather controls (Table 2.9). Standard errors are clustered at the household level. Table 2.9 shows a less than 1:1 relationship between changes in actual and theoretical energy use. Model 1 suggests that, on average, a 1 kWh/bimonth increase in theoretical energy use leads to a 0.47 kWh increase in actual bimonthly energy use. In Model 2 the theoretical EPC coefficient falls to 0.198 and features significant effects for dwelling size and weather covariates. A one square metre increase in dwelling size is associated with 8.69 kWh higher actual energy use, on average. Relative to a one floor dwelling, houses with a second floor, on average, use 548 kWh more each period. Results suggest that larger homes consume more energy and that actual energy use rises during colder periods.

Model 3 replaces the weather variables with a categorical time variable. Relative to November-December 2014, we observe lower actual use in spring/summer and higher energy use in autumn/winter. The coefficients for the EPC and dwelling features are largely unchanged. Models 1-3 also interact the continuous EPC with its categorical form.

Significant interactions in Model 1 suggest a heterogenous relationship between the continuous EPC and actual energy use, depending on the theoretical level of energy efficiency. Following AIC and BIC criteria, we consider Model 3 the most appropriate[16].

Table 2.9: Bimonthly Results – Continuous EPC ($AA_{Relative}$)

Dep Var: Actual energy use (kWh/bimonth)	Model 1		Model 2		Model 3	
	Coef.	SE	Coef.	SE	Coef.	SE
TQ (kWh/bimonth)	**0.466*****	**(0.042)**	**0.202*****	(0.063)	**0.222*****	(0.061)
EPC = AB (REF)						
C	-33.080	(67.636)	63.796	(69.185)	67.532	(66.217)
D	-50.590	(72.906)	132.875*	(76.916)	131.218*	(73.388)
E	**-204.105****	(94.404)	14.525	(99.869)	32.140	(95.389)
FG	35.592	(117.020)	109.705	(113.436)	71.718	(111.735)
TQ#AB (REF)						
TQ#C	**-0.100****	(0.048)	-0.027	(0.049)	-0.041	(0.047)
TQ#D	**-0.183*****	(0.047)	-0.071	(0.051)	-0.094*	(0.049)
TQ#E	**-0.185*****	(0.050)	-0.043	(0.057)	-0.076	(0.055)
TQ#FG	**-0.321*****	(0.049)	-0.102*	(0.059)	**-0.124****	(0.057)
Detached (REF)						
Apartment			5.487	(41.743)	-56.685	(39.239)
Semi-detached			-17.547	(32.802)	-47.427	(31.008)
Terrace			-18.061	(35.134)	-53.857	(33.098)
1 Floor (REF)						
2 Floors			**518.289*****	(33.150)	**492.860*****	(31.563)
3 Floors			**829.710*****	(46.477)	**784.223*****	(44.264)
4 Floors			**552.210*****	(206.635)	**483.133****	(193.952)
Floor area (m_2)			**8.480*****	(1.297)	**7.806*****	(1.235)
Year of construction			-0.040	(0.366)	-0.052	(0.344)
Living area percent			-2.032*	(1.103)	**-3.294*****	(1.055)
Heating Degree Days			**27.651*****	(0.313)		
Total precipitation (cm)			**23.491*****	(0.674)		
Bimonthly Time Dummy					**Yes**	Yes
Constant	**1024.657*****	(53.899)	-1425.67*	(751.461)	**1857.671*****	(707.585)
N	149,518		149,518		149,518	
r^2	0.028		0.112		0.255	
AIC	2634556		2621070		2594909	
BIC	2634655		2621278		2595246	

Asterisks note significance at the 10 (*), 5 (**), or 1 percent (***) level. Standard errors in brackets. Model 1 features a significant interaction for the continuous and categorical EPC independent variables.

[16] Appendix 2G confirms the relationship persists using a categorical version of theoretical energy use.

Results in Table 2.10 are obtained using the variant of actual energy use that features an absolute reduction in appliance use ($AA_{Absolute}$) are in line with those in Table 2.9. Every significant coefficient is larger in magnitude than before, reflecting a stronger association between theoretical energy use, dwelling characteristics and actual energy use.

Table 2.10: Bimonthly Results – Continuous EPC ($AA_{Absolute}$)

Dep Var: Actual energy use (kWh/bimonth)	Model 1_{Abs}		Model 2_{Abs}		Model 3_{Abs}	
	Coef.	SE	Coef.	SE	Coef.	SE
TQ (kWh/bimonth)	**0.586*****	(0.052)	**0.257*****	(0.077)	**0.282*****	(0.074)
EPC = AB (REF)						
C	-36.686	(83.897)	80.930	(85.970)	85.474	(82.242)
D	-50.335	(90.273)	172.676*	(95.467)	170.472*	(91.035)
E	**-234.916****	(117.127)	27.987	(124.325)	49.941	(118.660)
FG	69.487	(141.041)	154.345	(137.354)	106.771	(134.915)
TQ#AB (REF)						
TQ#C	**-0.126****	(0.060)	-0.035	(0.060)	-0.051	(0.058)
TQ#D	**-0.232*****	(0.058)	-0.091	(0.063)	**-0.120****	(0.061)
TQ#E	**-0.234*****	(0.062)	-0.055	(0.070)	-0.096	(0.067)
TQ#FG	**-0.407*****	(0.061)	-0.134*	(0.073)	**-0.162****	(0.070)
Detached (REF)						
Apartment			1.912	(51.753)	-75.859	(48.617)
Semi-detached			-26.190	(40.772)	-63.580*	(38.530)
Terrace			-28.773	(43.670)	-73.615*	(41.127)
1 Floor (REF)						
2 Floors			**640.371*****	(40.979)	**608.591*****	(38.963)
3 Floors			**1031.274*****	(57.534)	**974.431*****	(54.734)
4 Floors			**677.805*****	(255.956)	**591.653****	(240.308)
Floor area (m_2)			**10.473*****	(1.584)	**9.632*****	(1.504)
Year of construction			-0.180	(0.454)	-0.195	(0.426)
Living area percent			-2.413*	(1.368)	**-3.990*****	(1.307)
Heating Degree Days			**34.441*****	(0.390)		
Total precipitation (cm)			**29.411*****	(0.840)		
Bimonthly Time					**Yes**	Yes
Constant	**1009.958*****	(66.653)	-1770.902*	(933.531)	**2329.161*****	(878.001)
N	149,518		149,518		149,518	
r^2	0.029		0.113		0.257	
AIC	2,700,145		2,686,646		2,660,127	
BIC	2,700,244		2,686,855		2,660,464	

Asterisks note significance at the 10 (*), 5 (**), or 1 percent (***) level. Standard errors in brackets. Model 1 features a significant interaction for the continuous and categorical EPC independent variables.

2.4.3 Bimonthly results: Split by EPC

This section answers the third research question, which investigates whether the effects from Model 3 are heterogeneous across the levels of the EPC. These results are presented in Model 4, which splits the sample according to EPC (Table 2.11). Results show decreasing explanatory power for the least energy efficient dwellings. This finding is similar to van den Brom et al. (2018), who find their EPC to be more reliable for efficient households.

Table 2.11: Bimonthly Results – Continuous EPC, by EPC category ($AA_{Relative}$)

Dep Var: Actual energy use (kWh/bimonth)	Model 4 - EPC Label				
	AB	C	D	E	FG
TQ (kWh/bimonth)	**0.21****	**0.16****	0.10	**0.44*****	0.09*
	(0.09)	(0.06)	(0.08)	(0.13)	(0.04)
Detached (REF)					
Apartment	31.98	-82.10	-0.66	-57.27	-179.64
	(101.10)	(62.65)	(83.19)	(136.72)	(166.66)
Semi-detached	-97.60	**-110.07****	27.47	-48.44	117.17
	(79.59)	(46.16)	(61.41)	(111.91)	(116.53)
Terrace	-33.00	-76.90	-16.62	-53.52	-57.04
	(81.51)	(50.51)	(66.16)	(115.57)	(119.99)
1 Floor (REF)					
2 Floor	**357.15*****	**500.60*****	**598.68*****	**426.30*****	**441.32*****
	(114.05)	(51.35)	(54.03)	(87.08)	(100.78)
3 Floor	**673.08*****	**819.08*****	**725.50*****	**771.94*****	**708.54*****
	(133.47)	(67.14)	(91.89)	(146.46)	(189.89)
4 Floors	**1110.28*****	357.92	551.62*		
	(149.40)	(246.11)	(329.90)		
Floor area (m_2)	**7.45*****	**8.41*****	**9.84*****	-9.41	**8.32****
	(2.05)	(1.98)	(3.65)	(7.38)	(3.87)
Year built	-1.38	-0.58	0.01	**2.81*****	-1.94*
	(0.95)	(0.59)	(0.66)	(0.84)	(1.11)
Living area percent	**-12.06*****	**-3.86****	0.51	-3.93	-0.26
	(2.98)	(1.69)	(1.92)	(2.86)	(3.97)
Bimonthly Time	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Constant	3333.49*	**2764.72****	1605.77	**-3851.8****	**5548.46*****
	(2011.66)	(1184.99)	(1334.01)	(1658.07)	(2126.24)
N	20,116	64,456	37,506	15,897	11,543
r^2	0.273	0.260	0.255	0.265	0.219
AIC	346,797	1,113,643	651,925	277,468	203,840
BIC	346,995	1,113,879	652,147	277,659	204,023

Asterisks note significance at the 10 percent (*), 5 percent (**), or 1 percent (***) level. Standard errors in brackets.

Differences are observed in the magnitude of the coefficient for the continuous measure of theoretical energy use (EPC). Average effects range from 0.16 to 0.45, which differs from the same coefficient in Model 3 (0.22).

When split by EPC, dwelling type is only significantly lower for C-rated apartments and semi-detached houses. There are significant effects for dwelling size throughout and a significant floor area effect in all except E-rated homes, with larger average effects (8.15-9.78) than in the pooled Model 3 (8.13).

Using the alternative version of our dependent variable (absolute appliance adjustment), we see similar results (Table 2.12). Average effects range from 0.20 to 0.56, suggesting that changes in theoretical energy use are more closely related to changes in actual energy use. Although results at the bimonthly level do not prove the existence of an EPG (Section 2.4.1), they highlight the statistically significant role of the EPC, dwelling characteristics and seasonality when modelling actual energy use.

Table 2.12: Bimonthly Results – Continuous EPC, by EPC category ($AA_{Absolute}$)

Dep Var: Actual energy use (kWh/bimonth)	Model 4_{Abs} - EPC Label				
	AB	C	D	E	FG
EPC (kWh/bimonth)	**0.28*****	**0.20****	0.13	**0.56*****	0.09*
	(0.10)	(0.08)	(0.10)	(0.16)	(0.05)
Detached (REF)					
Apartment	46.28	-107.23	-9.15	-81.08	-238.90
	(125.04)	(78.08)	(103.02)	(170.65)	(199.12)
Semi-detached	-120.69	**-140.87****	30.48	-69.20	131.12
	(98.38)	(57.53)	(76.44)	(139.03)	(142.58)
Terrace	-38.88	-102.54	-25.43	-80.06	-84.14
	(101.16)	(62.95)	(82.25)	(143.65)	(146.65)
1 Floor (REF)					
2 Floor	**447.60*****	**617.86*****	**735.36*****	**528.56*****	**550.79*****
	(139.06)	(63.87)	(66.94)	(107.96)	(121.96)
3 Floor	**840.97*****	**1016.06*****	**903.99*****	**963.06*****	**889.66*****
	(162.93)	(83.37)	(114.67)	(181.54)	(230.83)
4 Floors	**1383.02*****	440.42	664.84		
	(183.26)	(305.80)	(409.67)		
Floor area (m_2)	**8.76*****	**10.44*****	**12.12*****	-12.54	**11.88****
	(2.48)	(2.47)	(4.54)	(9.17)	(4.65)
Year built	-1.74	-0.86	-0.14	**3.31*****	-2.47*
	(1.18)	(0.73)	(0.82)	(1.04)	(1.35)
Living area percent	**-14.99*****	**-4.75****	0.65	-4.52	0.35
	(3.66)	(2.11)	(2.38)	(3.54)	(4.85)
Bimonthly Time	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Constant	**5796.75****	**3779.70****	2025.20	**-4260.4****	**6792.98****
	(2473.12)	(1479.84)	(1658.99)	(2108.26)	(2681.35)
N	20,116	64,456	37,506	15,897	11,543
r2	0.276	0.262	0.257	0.267	0.223
AIC	355,463	1,141,976	668,373	284,384	208,743
BIC	355,660	1,142,212	668,595	284,575	208,927

Asterisks note significance at the 10 percent (*), 5 percent (**), or 1 percent (***) level. Standard errors in brackets.

2.5 Discussion

The key insight from this study is the striking lack of variation in average actual energy use across the sample (457 kWh/year). This suggests that occupant demand for energy may not be as responsive to dwelling energy efficiency, which has been observed in the energy use of commercial buildings (Better Buildings Partnership 2019). This study also finds evidence of an Energy Performance Gap (EPG) for the Irish EPC, with significant differences between actual and theoretical energy use. Annual actual energy use is below the theoretical level, with a mean deficit of 2,279 kWh/year (-17%) and a median deficit of 1,235 kWh/year (10.83%). By comparison, Cozza et al. (2020) find a median EPG of -11% and mean EPG of -6% for a sample of Swiss dwellings. In this study, the median EPG is similar (10.8%), but the mean difference is far greater (-17%). This confirms the presence of an EPG in the Irish context but suggests that the EPG may be larger.

The size of the EPG varies by the EPC level. For the most efficient homes, actual energy use exceeds theoretical, with an average difference in the range of 39.6% for AB-rated homes. For the least efficient homes, actual energy use is below theoretical, with an average deficit of 24% for D-rated homes, 39% for E-rated homes and 56% for FG-rated homes.

These results have significant policy implications, as a nationwide upgrade of dwelling energy efficiency may lead to unintended consequences, such as under-heating in the least efficient homes potentially leading to over-heating following any upgrade. This is an important consideration, as it may run counter to policy targets of reducing energy use (while accepting it would likely improve occupant comfort and wellbeing). This is especially relevant considering the fact that the Energy Performance Gap is widely accepted in the research community, but often ignored in policy discourse (Gram-Hanssen and Georg 2018).

Findings are in line with similar studies of the EPG (Cozza et al. 2020; Majcen et al. 2013; van den Brom et al. 2018). Similar to the observation of Delghust et al. (2015), this study emphasises the importance of accounting for electricity use, instead of limiting the focus strictly space and water heating (Scheer et al. 2013). This is especially important as homes become increasingly energy efficient and electricity reliant.

The lack of variation in energy use across dwelling of very different theoretical efficiency presents opportunities for research across households of differing dwelling energy efficiency and socioeconomic status. For example, it could be the case that occupants of energy efficient homes have paid a premium for a home that can be heated at a lower effective per-unit cost. Similarly, possible explanations for the under-heating observed in energy inefficient homes could be due to other barriers to energy use such as fuel poverty, which have been established in research elsewhere (Coyne et al. 2018).

Results at the bimonthly frequency indicate that a 1 kWh increase in bimonthly theoretical energy use is associated with a 0.222 kWh increase in actual energy usage, on average. Other results suggest the EPC broadly works as intended, with a less efficient EPC being associated with greater actual energy use, when also controlling for key dwelling characteristics and seasonality. The coefficient values for dwelling floor size (7.81 kWh/bimonth) indicate that larger homes tend to consume more energy. When split by EPC category, greater explanatory power for more efficient homes is observed. The model better explains variation for more efficient homes, suggesting there is greater uncertainty when modelling less efficient homes, a finding that is consistent with van den Brom et al. (2018).

Future work might seek to address some of the limitations of this study. One concern is that the actual energy data observed is understated if a home uses another fuel source, e.g. open wood burning stove. This is true of many studies that focus on one space heating fuel. In this study, this risk is minimized by focusing homes with either natural gas or electricity as their heating fuel. To address sample attrition that may arise from customers switching energy provider[17], criteria based on the number of readings, the level of missingness and for unrealistically low metered energy use is applied to ensure sufficient energy use is observed (see Appendix 2B). Customer switching could be addressed with access to data from more utilities. The addition of household socioeconomic information could help to explain the main result of a lack of variation in actual energy use across the sample. Finally, future research could seek to quantify changes in whole-home energy use before and following a home energy retrofit. This would require a dataset with metered energy use and EPCs pre- and post-retrofit.

[17] There were 26,154 electricity customer switches on average each month in 2017 (CRU 2018).

2.6 Concluding remarks

This paper investigates the difference between theoretical energy use denoted by a residential Energy Performance Certificate (EPC) with actual energy use for a sample of 9,923 households in Ireland from late 2014 to mid-2017. It is the first paper to test for the presence of an Energy Performance Gap using a measure of whole-home energy use for a non-social housing sample of dwellings that do not receive a retrofit. It focuses on homes heated by natural gas and electricity to profile whole-home energy use and capture fuel switching. Households that underwent a retrofit during the observed period are excluded from the sample in order to isolate the difference in actual energy use and the theoretical level created by the engineering-based model that informs the EPC.

Results show there is very little difference in actual average consumption for households across the EPC spectrum. There is a less than five per cent discrepancy (457 kWh/year) between the highest and lowest average value. This is a surprising observation which warrants further investigation to understand the factors underlying this result. Analysis within EPC bands shows evidence of an Energy Performance Gap (EPG), with lower-than-expected energy use for houses with low energy efficiency and higher-than-expected energy use for energy efficient houses. For more efficient homes (AB, C) the average difference ranges from +39% to -56% of the relevant EPC value. Less efficient homes (E, FG) feature actual energy use lower than predicted, with an average difference ranging from -23% to -56% below the relevant EPC. Results using a measure of actual energy use with an absolute deduction for appliance usage (instead of relative) display similar results.

Results are consistent with similar studies of the EPG that focused exclusively on social housing tenants (Majcen et al. 2013; van den Brom et al. 2018). Additional results show a heterogenous relationship between theoretical energy efficiency and actual energy use across EPC levels. This is consistent with prior work that found the EPC has less explanatory power for the least efficient homes (Cozza et al. 2020; Sunikka-blank and Galvin 2012; van den Brom et al. 2018) and for the 'prebound' effect (Cozza et al. 2020; Sunikka-blank and Galvin 2012).

Policymakers could seek to improve the EPC by including historical energy use information. This could be facilitated by the upcoming rollout of residential smart meters as part of the Climate Action Plan (Government of Ireland 2019). Since the Irish EPC is consistent with EU guidance, it is likely that the issues identified in this paper could be present in other contexts, especially in the UK, as the Irish EPC is based on the UK Standard Assessment Procedure for dwelling energy ratings (SEAI 2012) and a similar lack of variation in actual energy use has been observed in commercial buildings (Better Buildings Partnership 2019). Future work could include additional utilities, socioeconomic information and track occupants over time (as is done in a retrofit study by Aydin et al. (2017)) to minimise customer attrition and include additional relevant covariates. This would enable researchers to understand the factors causing differences in the most and least efficient homes.

2.A Constructing actual energy use variable

This paper tests for differences in actual energy use (AQ) with the theoretical level from the Irish residential EPC (TQ). Whenever actual energy use is mentioned, it applies to the created variable that is comparable to theoretical energy use (Equation 2.5). Actual meter readings are aggregated, weighted by the heatable floor area (per EPC) and account for the difference between 'primary' and 'delivered' energy use (per EPC). The actual energy use variable must be adjusted to reflect 'primary' energy consumed.

Per SEAI, 'primary' energy use includes the energy consumed in the house plus an overhead for energy used in its generation and transmission. 'Delivered' energy is only what is consumed within the home. In the SEAI database of 729,609 homes, 'primary' is 39% larger than 'delivered' on average. In the sample of 9,923 homes, 'primary' is 22% larger than 'delivered' on average (Figure 2.4). We then adjust it to only reflect energy for space and water heating, lighting and ventilation.

EPC

$$\mathrm{TQ_i} = \frac{\mathrm{PrimaryEnergy_i}}{\mathrm{HeatableFloorArea_i}} \tag{2.5}$$

Actual energy use

$$\mathrm{AQ_{it}} = \frac{\sum \mathrm{Meter\ readings_{it}}}{\mathrm{HeatableFloorArea_i}} * \frac{\mathrm{TotalPrimaryEnergy_i}}{\mathrm{TotalDeliveredEnergy_i}} * \mathrm{AA}_j \tag{2.6}$$

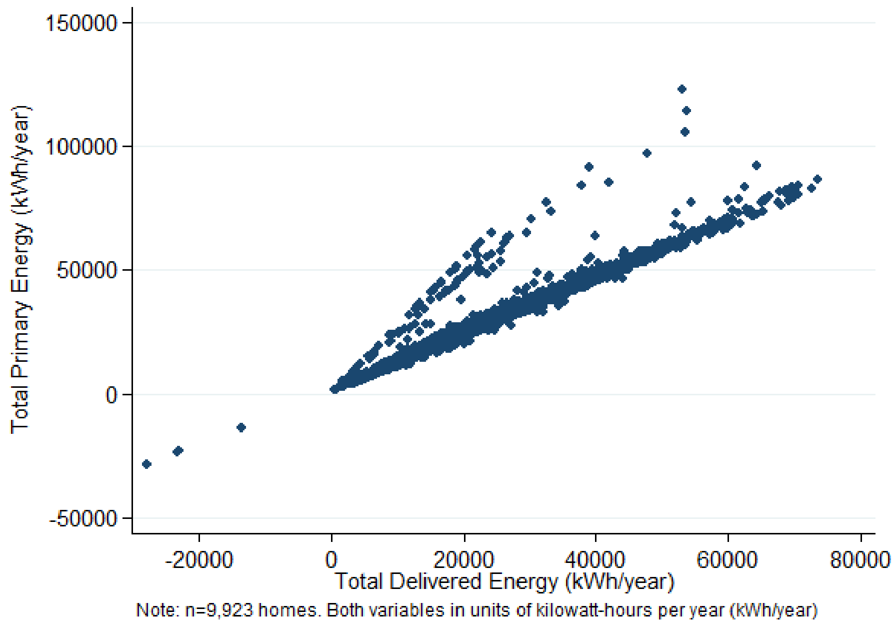


Figure 2.4: [2A] Sample scatter of Primary Energy v Delivered Energy

The EPC is based on heatable floor area (in kWh/m^2/year). Heatable and total floor area variables are present in the SEAI data. One source of sample attrition is that approximately 11% of dwellings in the SEAI database report a heatable floor area of zero, the majority being mid-floor apartments where heat loss is through the external wall (Table 2.13). These are excluded as they prevent the actual energy use variable from being constructed.

Table 2.13: [2A] Homes with zero floor area

	Apartment	Basement	Detached	Ground Apartment	Maisonette	Mid floor apartment	Top floor apartment	Total
Houses	2,359	2	1	815	2,357	42,276	33,406	81,216

Source: SEAI BER EPC Database (n=729,609)

Figure 2.5 compares the distribution of the continuous theoretical energy use (TQ) with the actual energy use (AQ) for the two full years observed (Y1, Y2). The distributions are within a similar range, which suggests that the removal of extreme values was successful.

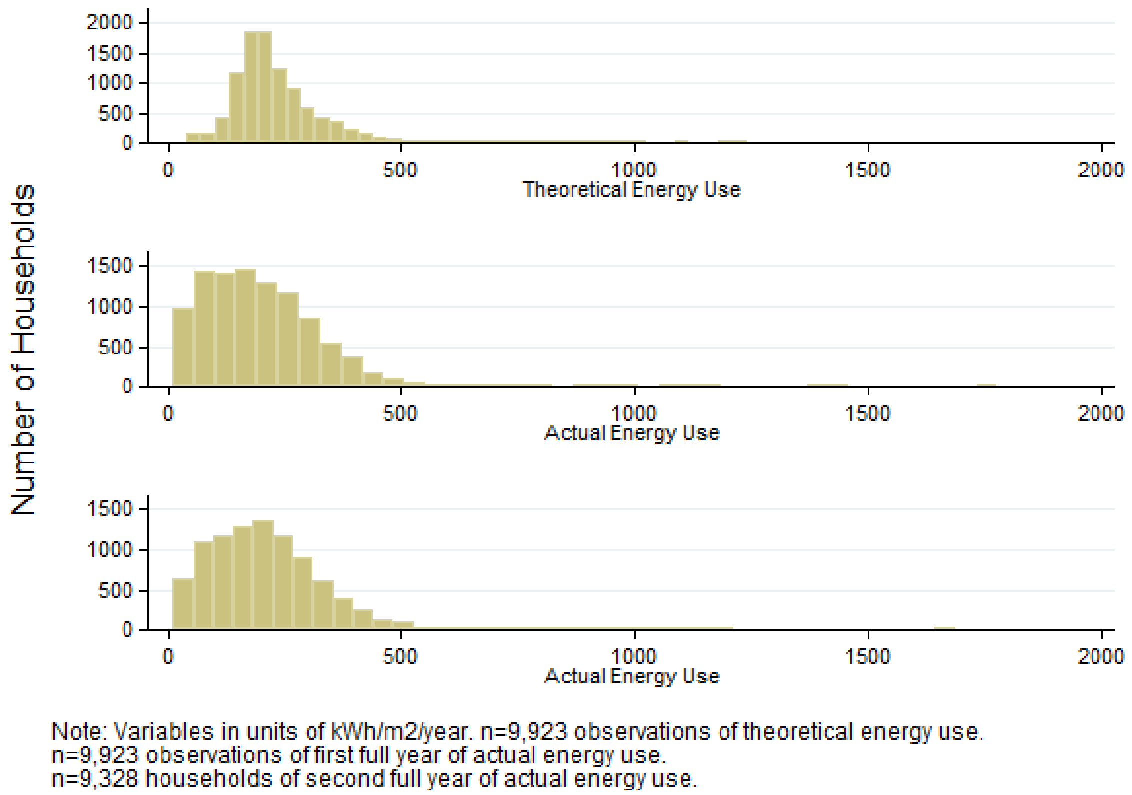


Figure 2.5: [2B] Distributions of continuous theoretical v actual energy use (Y1, Y2)

2.B Construction and cleaning of meter readings

This appendix summarises the steps taken to link, clean and filter the sample of residential energy use to reach a sample that is suitable for analysis.

1. Linking customers

- Gas fuelled homes are identified by linking Electric Ireland gas customer accounts with the corresponding Electric Ireland electricity account.
- Electricity accounts are anonymously merged with the SEAI dwelling data using the electric meter number (MPRN), which was unobservable to the research team.
- There are 286,523 unique customer matches between the original Electric Ireland measured energy use data and the SEAI dwelling data. Of this, 21,198 are unique matches for a gas customer account that is linked to an electricity customer account.

2. Energy data merge and sample restrictions

The original energy dataset features 30,045,696 daily energy readings (28,563,625 electricity, 1,482,071 gas) beginning November 2011. We drop households with no match in the SEAI dwelling data. Readings are aggregated bimonthly and adjusted to reflect the period of use e.g. A reading in March 2015 reflects usage in January 2015. Additional observations are dropped for the following reasons:

- Total household metered energy usage is zero.
- House is not heated by gas (per SEAI).
- Multiple meters for a house (per SEAI).
- A house received a grant-supported retrofit during the observed period (per SEAI).
- Drop electricity readings before the start of the gas sample (November 2014) to focus on the common period of electricity and gas use.
- A ratio of the number of missing periods to the number of periods present is created. This ratio is equal to 0.75 if a household is present for 16 periods but if missing for any four periods. Any household with a ratio less than 0.5 is dropped, which does not discriminate against homes that enter the data later.

- Drop any household with a gap between observations of at least six months. Although the customer might be present during the entire sample period, such a large missing period makes it unsuitable for analysis, especially for annual values.
- Drop any house with fewer than six observations (a full year of readings).
- Drop any house with an annual energy usage value (Y1, Y2) reading in the top or bottom one percent of the distribution to observe households with realistic energy use.
- Drop homes with an SEAI heatable floor area of less than 10m^2. Mostly apartments.
- Remove households with a Delivered Energy value in the top or bottom 1% of the distribution. As noted in Appendix 2.A, the SEAI dataset includes two variables of calculated annual use, one reflecting consumed energy (Delivered Energy) and the other including an overhead for energy generation (Primary Energy).

Table 2.14: [2B] Assumed appliance-specific electricity energy use

	Fridge-freezer	Oven	Microwave	Electric kettle	Toaster	Washing machine[1]	Vacuum	LCD TV	**Total**
Annual consumption (kWh)	427	290	56	167	22	178	18	199	**1,357**

Source: Owen & Foreman (2012). Note: Values used to construct $AA_{Absolute}$. [1] Values assume a multiple person household. The annual average lighting energy consumption of 548 kWh is disregarded in our analysis as the EPC accounts for lighting.

Table 2.15 compares dwelling characteristics for the initial sample (n=13,906) and the final sample (n=9,923) that is used for analysis in the body of the chapter. Based on this comparison, data cleaning did not change the profile of the sample in terms of theoretical dwelling energy efficiency and dwelling features.

Table 2.15: [2C] Initial Sample v Final Sample dwelling comparison

		Initial Sample (n=13,906)		**Final Sample (n=9,923)**	
		Count	**%**	**Count**	**%**
EPC	AB	1,998	14.37	1,351	13.61
	C	5,894	42.38	4,257	42.90
	D	3,369	24.23	2,486	25.05
	E	1,471	10.58	1,059	10.67
	FG	1,174	8.44	770	7.76
Dwelling Type	Detached	1,759	12.65	1,197	12.06
	Apartment	1,217	8.75	873	8.80
	Semi-detached	5,171	37.19	3,565	35.93
	Terrace	5,759	41.41	4,288	43.21
	Number of households	13,906	100	9,923	100
Dwelling Features		**Mean**	**SD**	**Mean**	**SD**
	Number of floors	1.96	0.48	1.94	0.48
	Year of Construction	1978	30	1979	28.98
	Percentage of home that is living area	21.24	9.93	21.33	9.81

2.C Weather and energy price controls

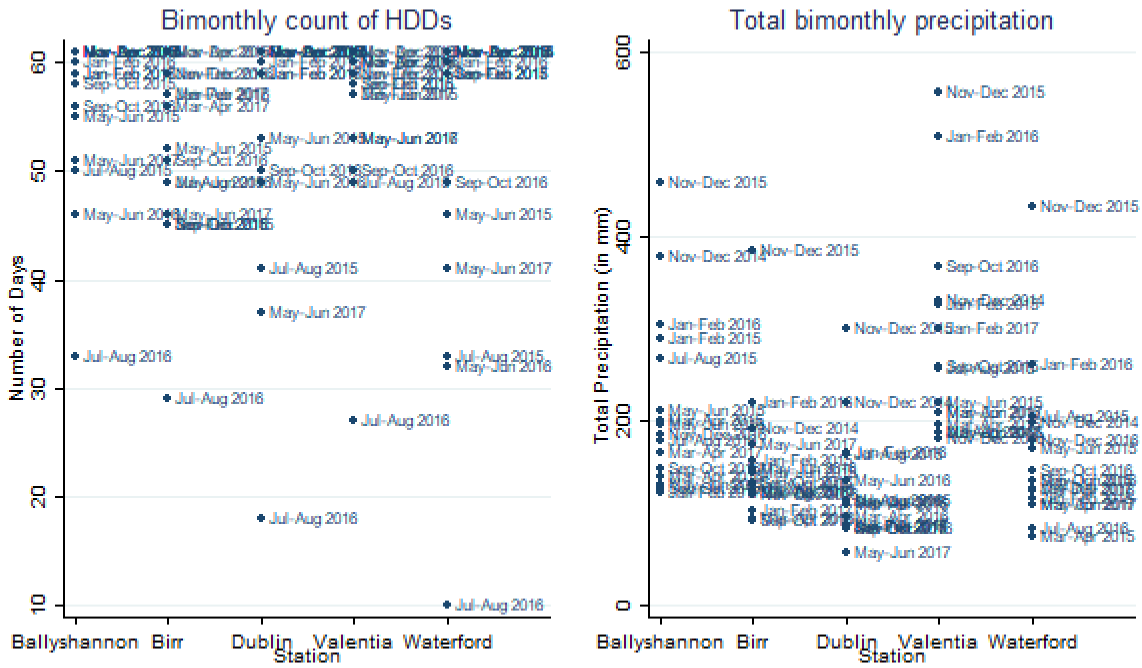


Figure 2.6: [2C] Bimonthly Heating Degree Days and Rainfall (by Station)

Source: Met Eireann. Note: A Heading Degree Day occurs when mean temperature is below 15.5 Celsius.

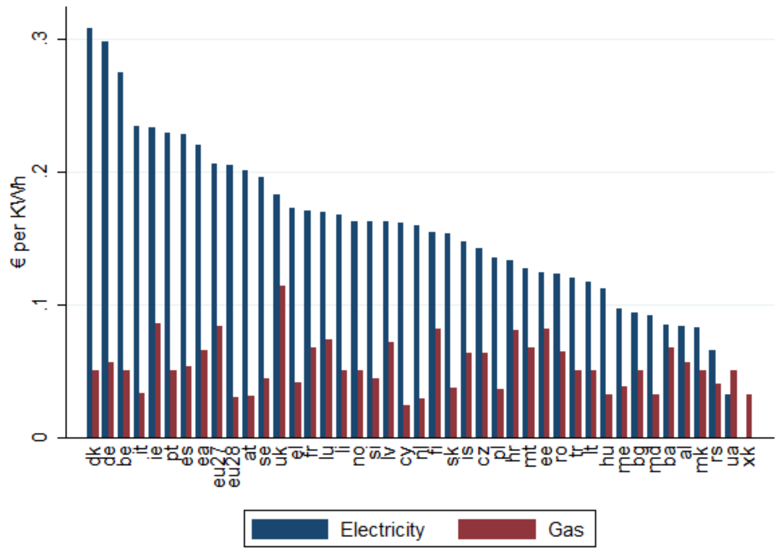


Figure 2.7: [2D] EU 2016 H2 electricity and gas price

Source: Eurostat H2 2016 Energy Prices

2.D The Irish utility regulator annual energy use benchmark

The Irish Commission for Regulation of Utilities (CRU) provides reference values for annual domestic energy use to be used by price comparison websites and energy providers. 2017 annual averages were set at 4,200kWh and 11,000kWh for electricity and natural gas, respectively. These are approximately 20% lower than the pre-2017 reference values. Table 16 shows the CRU annual means split by electricity meter type and dwelling type for gas.

The CRU observes average electricity use by tariff, with urban and rural 24HR tariffs below the national average. However, urban and rural Day/Night tariffs show an average above the national mean. The CRU gas data shows that the national average of 11,000 is higher than what would be expected for an apartment. Unfortunately, we cannot control for tariff type in our data. This underscores the need to consider appropriate reference points for annual national averages when considering our constructed variable of actual energy use and how it can vary by tariff and property type.

Table 2.16: [2D] CRU Average Energy Consumption

	Annual average electricity consumption (kWh)		Annual average gas consumption (kWh)
CRU Mean (2017)	4,200		11,000
Electricity Tariff Type		***Gas Dwelling Type***	
Urban 24HR	3,600 (-14%)	Apartment (1-3 bed)	7,000 (-46%)
Urban Day/Night Tariff	6,200 (+48%)	House (1-3 bed)	10,500 (-5%)
Rural 24HR	3,900 (-7%)	Large House (4-6 bed)	13,000 (+18%)
Rural Day/Night Tariff	12,000 (+286%)	Standalone Residential	15,000 (+36%)

Source: CRU Decision Paper CER/17042

2.E Robustness Check 1 – Annual results (Split by year of energy use)

This section provides a robustness check on the earlier test of significant differences between annual values of theoretical and actual energy use. The body of the paper aggregates 19,251 observations of actual annual energy use. Here we split the sample into 9,923 household-level observations for one full year of energy use and a further 9,328 observations of a second full year of energy use. Comparing Table 2.17 and Table 2.18, we observe a similar trend in differences between actual and theoretical energy use. Results for the second year of energy use feature a slightly smaller deficit between actual and theoretical energy use, with smaller deficits observed across every level of the EPC and property type. The only exception is the most energy efficient homes, with a slightly larger deficit for AB- and C-rated homes.

Table 2.17: [2E] Y1 difference between annual actual and theoretical energy use

	n	Mean AQ_{Y1}	Mean EPC	Difference	% Difference	SE	P-Value
$AQ_{All,Y1} - TQ$	9,923	10,532	13,152	-2,620	-19.92%	86	0***
EPC Grade							
AB	1,351	10,392	7,509	2,882	38.38%	171	0***
C	4,257	10,521	10,842	-322	-2.97%	100	0.002***
D	2,486	10,546	14,373	-3,827	-26.62%	147	0***
E	1,059	10,745	18,159	-7,414	-40.83%	246	0***
FG	770	10,499	24,990	-14,500	-58.02%	400	0***
Dwelling Type							
Apartment	873	7,914	11,625	-3,711	-31.92%	227	0***
Detached	1,197	13,261	19,323	-6,061	-31.37%	346	0***
Semi-detached	3,565	11,026	13,996	-2,970	-21.22%	140	0***
Terrace	4,288	9,892	11,039	-1,146	-10.38%	116	0***

***** P<0.01, **P<0.05, *P<0.10. Note: Sample of 9,923 homes with 9,923 observations of actual annual energy use (AQ) and 9,328 observations of a second year of energy use. Measured using AARelative dependent variable.**

Table 2.18: [2F] Y2 difference between annual actual and theoretical energy use

	n	Mean AQ_{Y2}	Mean EPC	Difference	% Difference	SE	P-Value
$AQ_{All,Y2} - TQ$	9,328	11,229	13,144	-1,916	-14.57%	87	0***
EPC Grade							
AB	1,250	10,761	7,637	3,124	40.90%	175	0***
C	4,012	11,262	10,808	453	4.20%	99	0***
D	2,349	11,309	14,332	-3,022	-21.09%	147	0.6
E	992	11,326	18,105	-6,778	-37.44%	242	0***
FG	725	11,458	24,932	-13,500	-54.15%	421	0***
Dwelling Type							
Apartment	801	8,333	11,563	-3,230	-27.93%	233	0.002***
Detached	1,119	14,194	19,451	-5,258	-27.03%	354	0.181
Semi-detached	3,340	11,796	14,021	-2,226	-15.87%	139	0***
Terrace	4,068	10,518	11,000	-483	-4.39%	117	0***

***** P<0.01, **P<0.05, *P<0.10. Note: Sample of 9,923 homes with 9,923 observations of actual annual energy use (AQ) and 9,328 observations of a second year of energy use. Measured using AARelative dependent variable.**

2.F Robustness Check 2 – Annual results (Split by sub-sample)

As noted in the body of the paper, the sample of 9,923 houses (149,518 readings) is divided across 8,311 houses (124,763 readings) that never receive a retrofit and a further 1,612 houses (24,755) that completed a retrofit prior to the start of our observed period of energy use. Results in the body of the paper report values for the entire sample, being explicit in how the sample excludes houses that change their dwelling energy efficiency over time. This appendix replicates those results, split by subsample, as a robustness check, to show no major discrepancy exists between houses in the sample (Table 2.19 and 2.20).

Table 2.19: [2G] Never Retrofit - Difference in annual actual and theoretical energy use

	n	Mean AQ	Mean EPC	Difference	% Difference	SE	P-Value
$AQ_{Control}$ – TQ	16,091	10,657	12,985	-2,327	-17.92%	68	0***
EPC Grade							
AB	2,317	10,205	7,087	3,118	43.99%	129	0***
C	6,590	10,604	10,346	258	2.49%	77	0.001***
D	3,861	10,711	14,045	-3,335	-23.74%	114	0***
E	1,858	11,081	17,995	-6,914	-38.42%	179	0***
FG	1,465	10,937	25,035	-14,100	-56.32%	294	0***
Dwelling Type							
Apartment	1,622	8,088	11,501	-3,413	-29.68%	165	0***
Detached	1,723	13,391	19,390	-5,998	-30.94%	301	0***
Semi-detached	5,485	11,207	14,041	-2,834	-20.18%	113	0***
Terrace	7,261	10,167	10,998	-831	-7.56%	90	0***

***** P<0.01, **P<0.05, *P<0.10. Note: Sample of 8,311 homes that never avail of a grant-supported retrofit. 8,311 observations of one year of actual energy use and a further 7,780 observations for the same houses with a second year of observed actual energy use. Measured using $AA_{Relative}$ variant of dependent variable.**

Table 2.20: [2H] Retrofitted - Difference in annual actual and theoretical energy use

	n	Mean AQ	Mean EPC	Difference	% Difference	SE	P-Value
$AQ_{Treated}$ – TQ	3,160	11,949	13,980	-2,031	-14.52%	138	0***
EPC Grade							
AB	284	13,540	11,517	2,023	17.57%	375	0***
C	1,679	11,966	12,711	-745	-5.86%	171	0***
D	974	11,735	15,573	-3,838	-24.65%	250	0***
E	193	10,495	19,456	-8,961	-46.06%	626	0***
FG	30	12,293	21,387	-9,094	-42.52%	1318	0***
Dwelling Type							
Apartment	52	8,954	14,544	-5,590	-38.44%	1043	0***
Detached	593	14,644	19,371	-4,728	-24.41%	408	0***
Semi-detached	1,420	12,135	13,879	-1,744	-12.57%	194	0***
Terrace	1,095	10,392	11,165	-772	-6.92%	196	0***

***** P<0.01, **P<0.05, *P<0.10. Note: Note: Sample of 1,612 homes that avail of a grant-supported retrofit before the period of energy use. 1,612 observations of one year of actual energy use and a further 1,548 observations for the same houses with a second year of observed actual energy use. Measured using $AA_{Relative}$ variant of dependent variable.**

2.G Robustness Check 3 – Bimonthly results using categorical EPC

In addition to the continuous version of the EPC, we model the categorical version of the EPC to observe associations (Table 2.21). This is performed in order to consider the average effect of a one unit increase in actual energy use for a change in the EPC. This is appealing if we believe that occupants know their EPC but are inattentive to the specific unit value. These results are consistent with those in the body of the paper using a continuous EPC and confirm that less efficient EPCs are associated with increasing levels of actual energy use.

Table 2.21: [2I] Bimonthly OLS results – Categorical EPC

Dep Var: Bimonthly measured energy use (kWh)	Model 5		Model 6		Model 7	
	Coef.	SE	Coef.	SE	Coef.	SE
EPC Label = AB	REF		REF		REF	
C	37.644	(26.467)	**152.072*****	(25.291)	**143.463*****	(23.823)
D	36.961	(28.886)	**224.829*****	(29.235)	**189.794*****	(27.623)
E	54.256	(35.535)	**277.004*****	(37.420)	**231.953*****	(35.467)
FG	49.832	(41.052)	**310.585*****	(44.758)	**241.323*****	(42.668)
Detached (REF)						
Apartment			-9.963	(41.907)	-72.374*	(39.406)
Semi-detached			-19.210	(32.817)	-49.929	(31.025)
Terrace			-26.649	(35.015)	-63.286*	(32.978)
1 Floor (REF)						
2 Floors			**491.419*****	(32.992)	**467.667*****	(31.387)
3 Floors			**794.670*****	(46.279)	**750.215*****	(44.048)
4 Floors			**508.383****	(201.707)	**443.997****	(190.195)
Floor area (m_2)			**13.923*****	(0.566)	**13.342*****	(0.540)
Year built			-0.374	(0.358)	-0.408	(0.336)
Living area percent			**-2.558****	(1.091)	**-3.708*****	(1.044)
Total Heating Degree Days			**27.656*****	(0.313)		
Total rainfall (cm)			**23.470*****	(0.676)		
Bimonthly Time					**YES**	YES
Constant	**1613.435*****	(23.329)	-805.289	(731.714)	**2537.047*****	(688.257)
N	149,518		149,518		149,518	
r2	0.000		0.111		0.254	
AIC	2,638,800		2,621,245		2,595,109	
BIC	2,638,849		2,621,404		2,595,396	

Asterisks note significance at the 10 percent (*), 5 percent (**), or 1 percent (***) level. Standard errors in brackets. Modelled using $AA_{Relative}$ variant of dependent variable.

2.H Robustness Check 4 – Fuel-specific results

Results in the body of this paper consider a measure of actual energy use that includes electricity and gas, while deflating to account for appliance use. This is designed to be comparable to the EPC. Many other studies of the EPG focus on the comparison between gas energy use and the EPC (Aydin et al. 2017; Cozza et al. 2020; Sunikka-blank and Galvin 2012). This section presents annual results that performs a t-test of means for gas. If this shows similar results to Section 2.4.1, this suggests that the evidence on the EPG observed is all due to a difference in gas consumption from the theoretical EPC level.

Table 2.22: [2J] Difference between annual Actual (AQ) and Theoretical (TQ) gas use ($AA_{Relative}$)

	n	Mean AQ	Mean TQ	Difference	% Difference	SE	P-Value
AQ_{All} – TQ	19251	9452.773	13148.1	-3695.331	-28%	64.591	0***
EPC Grade							
AB	2601	8979.353	7570.791	1408.562	19%	134.252	0***
C	8269	9279.777	10825.76	-1545.985	-14%	77.938	0***
D	4835	9628.3	14353.03	-4724.732	-33%	114.68	0***
E	2051	9990.076	18132.59	-8142.514	-45%	189.71	0***
FG	1495	9928.487	24961.51	-15000	-60%	303.971	0***
Dwelling Type							
Apartment	1674	6945.365	11595.13	-4649.767	-40%	177.632	0***
Detached	2316	12413.54	19384.96	-6971.412	-36%	259.594	0***
Semi-detached	6905	9990.711	14008.02	-4017.31	-29%	105.639	0***
Terrace	8356	8689.943	11019.98	-2330.038	-21%	86.446	0***

***** P<0.01, **P<0.05, *P<0.10. Note: Units in kWh/year. Sample features 9,923 observations of one year of actual GAS use and a further 9,328 observations from the same sample of houses with a second year of actual GAS use. A test of equality of medians (using signtest STATA command (Snedecor & Cochran, 1989), confirms the same differences exist.**

Table 2.22 highlights that the average EPG is 28% when only studying gas energy use. This is almost larger than the average deficit in the body for total energy use (-17%). Interestingly, a similar negative relationship exists between the size of the deficit and energy efficiency (+19% for AB, -68% for FG). This result suggests that estimates of the EPG that do not account for electricity use in the home may be overstating the true EPG as they do not account for fuel switching. This is especially the case for homes with the lowest energy efficiency. The sample average deficit of 28% is in line with estimates of rebound effects observed in other contexts (Sorrell et al. 2009).

Although Table 2.22 made a suitable comparison between gas energy use and the EPC), Table 2.23 is difficult to interpret because electricity use in the home was never intended to be the sole determinant of the EPC (which reflects space and water heating). As such, the average deficits are large negative values. This makes sense, as electricity is more commonly used as a secondary fuel in this sample, in association with gas heating.

Table 2.23: [2K] Difference in annual Actual (AQ) and Theoretical (TQ) electricity use ($AA_{Absolute}$)

	n	Mean AQ	Mean EPC	Difference	% Difference	SE	P-Value
AQ_{All} – TQ	19251	4134	13148	-9014	-69%	53	0***
EPC Grade							
AB	2601	4232	7571	-3339	-44%	81	0***
C	8269	4321	10826	-6505	-60%	51	0***
D	4835	4018	14353	-10300	-72%	81	0***
E	2051	3793	18133	-14300	-79%	147	0***
FG	1495	3777	24962	-21200	-85%	272	0***
Dwelling Type							
Apartment	1674	3198	11595	-8397	-72%	126	0***
Detached	2316	4726	19385	-14700	-76%	222	0***
Semi-detached	6905	4257	14008	-9751	-70%	82	0***
Terrace	8356	4056	11020	-6964	-63%	67	0***

***** P<0.01, **P<0.05, *P<0.10. Note: Sample of 9,923 homes with 9,923 observations of one year of actual ELECTRICITY use and a further 9,328 observations for the same houses with a second year of observed actual ELECTRICITY use. A test of equality of medians (using signtest STATA command (Snedecor & Cochran, 1989), confirms the same differences exist.**

Chapter 3: Evaluating a national residential energy efficiency subsidy using whole-home energy use data

3.1 Introduction

In the EU, buildings are responsible for roughly 40% of energy use and 36% of CO2 emissions (European Commission, 2019). Although new building regulations drive improved efficiency for new builds, upgrading the efficiency of the existing building stock is an important goal. It is especially important since approximately 75% of buildings are energy inefficient and only 0.4-1.2% of the building stock is renovated annually, depending on the country (European Commission, 2019). The residential sector represents 25.4% of final energy use in the EU in 2016. Many policies aim to improve the efficiency of space and water heating, which is responsible for 79.2% of residential energy use on average in the EU (Eurostat, 2019).

Influential evidence from US studies note that although subsidies of energy efficiency could improve welfare, their current calibration does not represent value for money or deliver expected savings (Allcott and Greenstone, 2017; Fowlie et al., 2018). As noted by Fowlie et al. (2018), many energy efficiency investments offer a win-win outcome, paying for themselves through energy use savings, while also decreasing emissions and improving health and comfort (Schwarz and Taylor, 1995).

Studies of the external benefits of energy efficiency present the case for subsidised energy efficiency, especially for renovating existing dwellings. However, reality often deviates from the social optimum. Jaffe and Stavins (1994) present the ‘Energy Efficiency Gap’ theory, where society features an under-adoption of energy efficient technologies with a positive net present value. Gerarden et al. (2015) identify three main areas that help to explain the lack of adoption of energy efficiency: Market failures, behavioural factors and model measurement error. Allcott & Greenstone (2012) note that evidence on the Energy Efficiency Gap is often situation specific, with measured savings often lower than engineering-based estimates.

In many residential retrofit settings, ‘rebound’ effects may occur when occupants consume a portion of the savings delivered by retrofit (Sorrell et al., 2009). Policymakers that intend to subsidize retrofit only to achieve savings in energy use to achieve national targets may be disappointed by the savings if rebound is present. However, many retrofit subsidy policies feature multiple objectives, including improving occupant comfort and wellbeing (Coyne et al. 2018; Ryan and Campbell 2012).

This study measures the extent to which domestic retrofit delivers real energy savings in Ireland. It is motivated by a policy target to upgrade a half a million homes to a specific EPC standard (B2) by 2030 (Government of Ireland, 2019)) and the mixed empirical evidence to date from other contexts. According to the Sustainable Energy Authority of Ireland (SEAI, 2019), Ireland is second last out of 28 EU countries in decarbonising heating, primarily due to the spatially dispersed nature of dwellings. By late 2019, a residential energy efficiency subsidy scheme has been adopted by 376,218 homes (18% of the 2016 national dwelling stock of 2,003,645)[18]. Despite this, Ireland is set to miss its targeted 20% improvement in energy efficiency, relative to 2005 levels, with savings of 16%.

This paper makes several important contributions. It is one of the largest studies of retrofit using whole-home energy use data for a non-social housing sample. This is important to quantify the effectiveness of retrofit without focusing on a sample that disproportionately experiences fuel poverty (Fowlie et al., 2018). Secondly, it uses whole-home energy data (i.e. electricity and gas meter readings) to capture potential spill overs between fuel sources due to retrofit. This is not captured in other papers examining retrofit effectiveness (Coyne et al., 2018; Scheer et al., 2013).

Finally, this study addresses concerns regarding self-selection issues associated with the decision to undergo a retrofit. Most studies of retrofit compare a treatment group that receives a subsidy and a control group that do not (Fowlie et al., 2018; Scheer et al., 2013).

[18] See https://www.seai.ie/grants/home-energy-grants/home-upgrades/home-energy-upgrades-by-county.pdf

In the absence of experimental variation, this study considers two control groups: homes that never receive a retrofit (consistent with prior literature) and a second control group of homes that received a retrofit prior to the observation period. This helps account for potential self-selection issues related to the choice to undergo a retrofit.

The rest of this study is laid out as follows: Section 3.2 details relevant literature. Section 3.3 provides context to the case study. Section 3.4 details the conceptual framework, states the research questions and details the empirical strategy. Section 3.5 describes the dataset while Section 3.6 presents results. Section 3.7 concludes by discussing policy implications.

3.2 Related Literature

This section summarises notable studies of retrofit, many of which are concerned with rebound effects that causes actual savings to deviate from the level expected. Other literature which considers the multiple benefits of retrofit are also discussed.

3.2.1 The effectiveness of retrofit

Studies of retrofit have identified rebound effects, where improvements in dwelling energy efficiency lower the effective cost of domestic energy services and result in increased energy use post-retrofit (Sorrell et al., 2009). Rebound effects have the potential to undermine the intent of policies that subsidise retrofit (Gerarden et al., 2015). Such retrofit policies aim to overcome the investment inefficiencies that comprise part of the Energy Efficiency Gap (Jaffe and Stavins, 1994). As noted by Aydin et al. (2017), uncertainty regarding the actual size of rebound makes it difficult to include when formulating energy efficiency policies.

The level of rebound has been shown to vary across contexts, with effects ranging from 0% to 100%, with an average long run rebound of 30% (Sorrell et al., 2009). Sanders and Phillipson (2006) find that only 50% of expected savings are realised, with temperature take-back responsible for 15% of the shortfall. In the UK, Dowson et al. (2012) note that predicted savings from a model may be halved in reality due to poor installation, monitoring and the increased use of heating (i.e. rebound) following refurbishment.

Aydin et al. (2017) highlight some of the factors causing rebound to differ, with homeowners (26.7%) rebounding less than tenants (41.3%). They also find significant heterogeneity in rebound depending on household income, with low-income households displaying a higher rebound effect than other cohorts. This is likely due to fuel poverty, detailed in the next section as a qualitative motivation for retrofit.

Fowlie et al. (2018) outline the extent of the rebound issue in an analysis of 30,000 US low-income homes. They suggest that upfront investment costs are about twice the actual energy savings and model-projected savings are more than three times larger than actual savings. Even after accounting for rebound (which they observe little of) and societal benefits from reduced emissions they find an average annual rate of return of approximately -7.8%. In a study of subsidised heat-pumps in the USA, Alberini et al. (2016) show that average energy savings of 8% are driven by an average 16% saving from adopters without rebate and average savings close to zero for those that received a rebate. This serves as a note of caution to policymakers about the importance of calibrating policies correctly.

Despite the generally bleak consensus around the ability of energy-related subsidies to achieve results, there is hope. Allcott & Greenstone (2017) evaluate the welfare effects of a randomly assigned subsidy towards home energy audits. They find unobserved benefits and costs, with realized energy savings only 58% of the level predicted. They estimate that average gas savings after retrofit are only 29% of the level predicted by an engineering-based model. Without proper subsidy calibration, societal welfare is net negative. However, there is potential to improve welfare if the subsidy is better calibrated. The evidence to date on residential energy efficiency schemes suggests they do not appear to deliver on their promise of achieving stated reductions in energy use. This is mainly due to human behaviour deviating from engineering model-based estimates (Allcott and Greenstone, 2012).

3.2.2 The multiple benefits of retrofit

Like many energy efficiency policies, a subsidised retrofit may seek to achieve multiple aims, lowering energy use while also increasing occupant comfort (Ryan and Campbell 2012). Evidence suggests that homeowners considering a retrofit are influenced by potential energy savings, the private cost of investment and comfort gain, respectively (Aravena et al. 2016). Environmental benefits are a by-product of lower energy use.

The multiple benefits of retrofit are pronounced when policies target social housing tenants who experience fuel poverty (Coyne et al. 2018; Fowlie et al. 2018). In a study of social housing tenants (n=94), Coyne et al. (2018) note that there is an average 30% shortfall between the expected and actual change in energy use, which underlines the important role of occupant behaviour in realising the expected energy savings.

Although much attention is given to the qualitative benefit of retrofit, consideration should be given to the negative qualitative consequences. Collins & Dempsey (2019) detail international case studies of the unintended consequences of retrofit, suggesting that increased air tightness can lead to higher levels of radon gas and increased mould growth. In a separate study of social housing tenants, improved cavity wall insulation increased indoor temperatures and occupant comfort but also increased pollutants (Broderick et al. 2017).

It is likely that indirect benefits and consequences help inform decisions to subsidise retrofits. In this sense, studies that focus on changes in energy use following a retrofit likely provide a lower bound estimate of total societal welfare. From the narrow perspective of reducing energy use, studies that focus exclusively on social housing tenants run the risk of presenting a pessimistic view on the energy savings of retrofit, as occupants are more likely to consume their energy savings.

3.3 Case study context: Ireland

This study quantifies actual changes in whole-home energy use for a non-social housing sample of Irish households. This section provides context to the research setting, including key policies and relevant research to date.

3.3.1 Residential energy efficiency in Ireland

The EU set 2030 climate targets to i) source 32% of the energy mix from renewable sources, ii) reduce greenhouse gas emissions by 40% from 1990 levels and iii) improve energy efficiency by 32.5%, relative to a 2007 forecast of 2030 energy use (European Parliament, 2018). As part of this, Ireland aims to improve energy efficiency by 20% before 2020 relative to average national energy use from the period 2001-2005, equating to energy savings of 31,925 GWh (DCENR, 2009).

By early 2017 Ireland has only achieved a 12% improvement in energy efficiency and is expected to miss the 2020 target by 3.77% (DCCAE, 2017), with compliance penalties potentially costing €80-140 million (Deane, 2017).

Ireland is an ideal case study because it features the third highest per-capita emissions in the EU[19], despite energy consumed per dwelling falling by 32% from 1990-2015 due to increased retrofits, improved building regulations and macroeconomic factors (SEAI, 2016). Secondly, Ireland has an ambitious plan to improve residential energy efficiency by retrofitting half a million homes (a quarter of the 2016 national dwelling stock[20]) to a high B2 EPC standard by 2030. Other targets include the installation of smart meters in every home by 2024 to improve demand side responsiveness (Government of Ireland, 2019).

Ireland also expects to reduce residential emissions by transitioning to natural gas use, which is considered a ‘clean’ fossil fuel that emits 40% less CO2 than coal and 22% less CO2 than oil (Government of Ireland, 2019). Gas currently represents 21.7% of Ireland’s final energy consumption in the residential sector, 12th highest in EU-28 (Eurostat, 2019). By contrast, Ireland is highest in the EU-28 in terms of oil (38.9%) and second highest for solid fuel (11.7%). Gas is viewed as a low-carbon transition fuel that could accommodate hydrogen and biomethane by 2050 (GNI, 2019). It is present in 700,000 Irish houses, with 300,000 potential customers close to the network who mostly use oil (Ervia, 2018). Analysis suggests that decarbonising heating for the one million homes on or close to the gas network is three times cheaper with renewable gas than it is for electrification (Ervia, 2018).

3.3.2 SEAI and the Better Energy Homes grant

The Sustainable Energy Authority of Ireland (SEAI) administers energy efficiency policy supports in Ireland. Since 2009, this includes the residential Better Energy Homes grant, where measures are approved by a registered contractor and inspected following completion. As of June 2018, 219,988 homes availed of the grant with a total subsidy of €225 million[21]. Table 3.1 details the most recent grant levels, with bonus payments for adopting three or four measures. Measures generally include insulation or a boiler replacement.

[19] See https://www.cso.ie/en/releasesandpublications/ep/p-eii/eii19/mainfindings/
[20] See https://www.cso.ie/en/releasesandpublications/ep/p-cp1hii/cp1hii/hs/
[21] See https://www.seai.ie/data-and-insights/seai-statistics/better-energy-home-statistics/

Table 3.1: Better Energy Homes grant payment levels

Measure	Category	Grant value (€) from March 2015
Roof	Attic Insulation	300
Wall	Cavity wall insulation	300
	Internal dry-lining[1]	1200/1800/2400
	External wall insulation[1]	2250/3400/4500
Boiler	High efficiency boiler (oil / gas) with heating controls	700
	Heating controls upgrade only	600
Solar	Solar heating	1200
BER	Mandatory Pre- and Post-Retrofit Audit	50
Bonus	Three measures	300
	Four measures	100

Source: Collins & Curtis (2016). Note: [1] Values for Apartment / Semi-Detached / Detached houses, respectively. A version of this table including prior iterations of the scheme is present in Appendix 3.A.

SEAI manage the Building Energy Rating (BER) EPC that is required for properties that are sold, rented or receive a grant-supported retrofit (European Union, 2002). The EPC reflects theoretical energy use for space and water heating, ventilation and lighting while making assumptions regarding occupant behaviour. Table 3.2 shows the categories of the EPC.

Table 3.2: Energy Performance Certificate (EPC) levels

EPC	A1	A2	A3	B1	B2	B3	C1	C2	C3	D1	D2	E1	E2	F	G
Min	0	25	50	75	100	125	150	175	200	225	250	300	340	380	450
Max	25	49	74	99	124	149	174	199	224	249	299	339	379	449	

Source: SEAI. Note: Minimum and Maximum values in $kWh/m^2/year$.

The EPC is influenced by dwelling factors such as size, type and heating source (SEAI, 2014) and discloses theoretical energy performance in units of kilowatt-hour per metre squared per annum (kWh/m2/year). This performance is based on ‘primary’ energy use, defined as energy delivered plus an overhead for generation and transmission losses. It does not include appliance energy use, which estimated at 20% of energy use (SEAI, 2018).

3.3.3 Studies of the Better Energy Homes grant

Collins and Curtis (2017) examine the value for money of the Better Energy Homes grant by studying grant levels and expected changes in energy use. They find that retrofitting less efficient homes, larger homes and homes with less air circulation provide greater net benefit.

They also assert that retrofits including attic and cavity wall insulation and boiler upgrades provide the greatest benefit, while solid and external wall insulation provides less value. Work by Scheer et al. (2013) study the same grant, finding an average shortfall of 36% between theoretical and actual gas use for an Irish sample (n=210).

This study improves on prior research by focusing on actual changes in whole-home energy use. Scheer et al. (2013) study changes in domestic gas usage but do not account for electricity used by households. This omits significant energy use in the household. Collins and Curtis (2017) estimate the value for money of specific retrofit measures but fail to account for changes in actual energy use, relying solely on the change in theoretical energy use denoted by EPCs. This does not account for changes in actual energy use, which may deviate from the theoretical level.

By focusing on changes in whole-home energy use, this paper addresses two key aspects of understanding the total effect of a retrofit: calculating the actual change in total energy use and quantifying the actual value for money of a retrofit represents.

3.4 Conceptual framework

Although a national retrofit scheme aims to improve energy efficiency, there are behavioural and market-driven factors which may limit adoption - creating an Energy Efficiency Gap (Jaffe and Stavins, 1994). Allcott & Greenstone (2012) detail how policies that i) reduce investment inefficiencies or ii) incorporate energy use externalities can help shift demand towards a more socially optimal level. Through this lens, a subsidy towards home energy retrofit can be viewed as an attempt to reduce investment inefficiencies.

Fowlie et al. (2018) note how an individual privately benefits from improving home energy efficiency. Firstly, a more efficient home reduces energy use. Secondly, it increases consumption of energy services within the home, as it is now a lower effective price following the retrofit (i.e. rebound). From a social perspective, rebound improves consumer wellbeing through increased heating and comfort.

If the policymaker's sole objective is to lower energy use, it is important to study actual changes in energy use, where consumer behaviour could deviate from the expected change. Furthermore, if consumers are availing of a subsidized home energy retrofit, the state is effectively financing the additional energy use of households, creating an additional barrier to meeting energy efficiency targets.

3.4.1 Research questions

This study has three specific research questions. The first research question tests whether receiving a retrofit lowers actual energy use. Equation 3.1 presents the null hypothesis that actual total household energy use does not change following retrofit. The alternative hypothesis states that actual energy use following retrofit is different to the level of energy use prior to retrofit. Rejection of the null hypothesis is to be expected. However, it is an important question to answer given that other studies suggest that actual energy use could increase (Heesen and Madlener 2018; Sorrell et al. 2009) or decrease (Cozza et al. 2020; Sunikka-blank and Galvin 2012) following a retrofit. Results test this hypothesis in multiple ways using a binary measure of retrofit and by focusing on specific combinations of measures. This is motivated by previous work that shows different retrofit measures deliver different reductions in energy use (Collins and Curtis 2017).

$$H0: EA_{i,PreRet} = EA_{i,PostRet} \qquad [3.1]$$

$$HA: EA_{i,PreRet} \neq EA_{i,PostRet}$$

The second research question investigates the extent to which actual energy use approximates the theoretical level of energy use denoted by an EPC. This is important for policymakers attempting to reach savings in actual energy use by setting national EPC targets (Government of Ireland 2019). Equation 3.2 details the null hypothesis, where there is no difference in actual and EPC-based energy use, measured at the bimonthly frequency[22].

$$H0: EA_{i,t} = ET_{i,t} \qquad [3.2]$$

$$H0: EA_{i,t} \neq ET_{i,t}$$

[22] The term 'bimonthly' denotes a period of two months. This is not to be confused with the 'twice-monthly' frequency.

The third research question of this study quantifies the value for money that combinations of retrofit measures deliver. A comparison is drawn between *expected* value for money, denoted by the cost of achieving changes in theoretical energy use, and *actual* value for money, denoted by changes in actual energy use. Equation 3.3 states the null hypothesis that features no difference between expected and actual value for money for a specific retrofit.

$$H0: eVFM_{HH} = aVFM_{HH} \qquad [3.3]$$
$$HA: eVFM_{HH} \neq aVFM_{HH}$$

3.4.2 Empirical strategy

Similar to Fowlie et al. (2018), this study uses a difference-in-differences approach to estimate the benefit of a retrofit received. Equation 3.4 details how (for household i in bimonth m and year t) energy use (E_{imt}) is modelled as a function of the decision to receive a retrofit (D_{imt}). Additional covariates include household-by-bimonth fixed effects (α_{im}) to control for household-specific differences and a group of bimonth-by-year fixed effects (α_{mt}) to adjust for average time effects, such as weather. The coefficient β_1 captures the mean difference in energy use from the retrofit, after accounting for the fixed effects. Fowlie et al. (2018) obtain unbiased estimates by randomizing encouragement to undergo a retrofit and by studying a sample of participants that households that applied for the subsidized retrofit but had not received it by the end of the observation period.

$$ln(E_{imt}) = \beta_1 D_{ismt} + +\alpha_{im} + \alpha_{mt} + \epsilon_{imt} \qquad [3.4]$$

This paper performs a generalised difference-in-differences (Equation 3.5) across three subsamples (Control (CL), Already Treated (AT) and Treatment (TR)) to account for self-selection bias in the retrofit adoption choice. For household *i* in subsample *s*, bimonth *m* and year *t*, actual energy use (EA_{ismt}) is modelled as a function of receiving a retrofit (D_{ismt}), household fixed effects (α_{im}) to control for household-specific differences and a group of bimonth-by-year fixed effects (α_{mt}) to adjust for average time effects. The OLS estimate of the coefficient β_1 reflects the estimated impact of the retrofit on actual energy use.

$$EA_{ismt} = \beta_1 D_{ismt} + \alpha_{im} + \alpha_{mt} + \epsilon_{imt} \qquad [3.5]$$

3.5 Data description

3.5.1 Data sources

This study compares theoretical energy use from an EPC with meter readings for a large sample of Irish households. Per Table 3.3, metered electricity and gas data are sourced from Electric Ireland, the largest residential electricity utility. Dwelling characteristics and EPCs are obtained from a public SEAI database. A separate SEAI database provides information on retrofits. These are merged using an anonymous identifier based on the unique electricity meter for each dwelling. Data is observed for the period November 2014 to June 2017, sixteen bimonthly periods. Data is also collected for time-varying weather controls.

Table 3.3: Data sources

ID	Data	Details	Source
A	Energy use	Electricity and gas readings	Electric Ireland
B	Building Energy Rating	Dwelling features, EPC	SEAI
C	Better Energy Homes	Retrofit measures and costs	SEAI
D	Weather	Heating degree days, rainfall	Met Eireann

Note: Appendix 3.B details the data cleaning process and the handling of unreliable data.

3.5.2 Sample dwelling information

The dataset features a balanced panel of 7,832 households (n=125,312 bimonthly readings). Table 3.4 summarises three subsamples: Control (CL) households never receive a retrofit. Already Treated (AT) households have a recorded retrofit before the period of observed energy use. Treatment (TR) households undergo a retrofit during the observation period.

Table 3.4: Sample classification

Sub-sample	Number of houses	Bimonthly Observations
Control (CL)	5,982	95,712
Treated (AT)	1,279	20,464
Treatment (TR)	571	9,136
Total	**7,832**	**125,312**

Source: Author's calculations. Houses feature measured energy use from November 2014-June 2017.

Table 3.5 compares sample representativeness. Compared to the SEAI EPC Population, the Full Sample has a higher share of B-rated and C-rated houses and a lower share across other EPC bands.

The Full Sample under-represents detached homes and apartments and over-represents semi-detached and terraced[23]. In the Full Sample, there is a larger share of C-rated homes in both the AT and TR groups, relative to the CL group. CL group has a larger share of apartments and terraced houses. Compared to the 2016 national dwelling stock, SEAI EPC population data underrepresents detached dwellings, overrepresents apartments and terrace homes. This is likely since an EPC is required when a property is sold or undergoes a retrofit. The focus on gas-connected dwellings partly explains the under-representation of detached dwellings, which are more likely to be fuelled by oil or solid fuel.

Table 3.5: Comparison of sample, EPC population and national dwelling stock

	Full Sample (n=7,832)		**Control CL (n=5,982)**		**Already Treated AT (n=1,279)**		**Treatment TR (n=571)**		**SEAI EPC Population (n=729,599)**		**National Dwelling Stock (n=1,675,795)***	
EPC	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**
A1									41	0.01		
A2	10	0.13	10	0.17					4,368	0.6		
A3	61	0.78	61	1.02					16,212	2.22		
B1	104	1.33	100	1.67	2	0.16	2	0.35	9,083	1.24		
B2	240	3.06	215	3.59	17	1.33	8	1.4	21,772	2.98		
B3	613	7.83	458	7.66	96	7.51	59	10.33	52,608	7.21		
C1	1,100	14.04	802	13.41	181	14.15	117	20.49	81,450	11.16		
C2	1,262	16.11	880	14.71	254	19.86	128	22.42	94,673	12.98		
C3	1,148	14.66	805	13.46	248	19.39	95	16.64	94,502	12.95		
D1	1,105	14.11	776	12.97	251	19.62	78	13.66	95,190	13.05		
D2	839	10.71	648	10.83	141	11.02	50	8.76	82,980	11.37		
E1	464	5.92	386	6.45	55	4.3	23	4.03	48,364	6.63		
E2	337	4.3	306	5.12	23	1.8	8	1.4	38,036	5.21		
F	320	4.09	308	5.15	9	0.7	3	0.53	38,416	5.27		
G	229	2.92	227	3.79	2	0.16			51,904	7.11		
Dwelling Type												
Detached	1,327	12	897	11	300	19	130	16	232,677	32	715,133	43
Apartment	890	8	846	10	27	2	17	2	144,289	20	204,145	12
Semi-D	3,999	37	2,840	34	725	45	434	53	193,543	27	471,948	28
Terrace	4,527	42	3,728	45	560	35	239	29	159,100	22	284,569	17

Source: Author's calculations based on SEAI BEH and EPC data and 2016 Census. 2016 Census values include occupied households, excluding 'Not stated' and temporary accommodation. Note: Semi-D refers to dwellings considered as a semi-detached or end of terrace dwelling.

[23] The under-representation of apartments is because most apartments have zero heatable floor space. This makes them incompatible with this study, which constructs a measured energy use variable using floor area.

Table 3.6 summarises key dwelling features of the sample. The average year of construction in the Full Sample is 1979. On average, the TR and AT homes are larger, older and have a smaller fraction of the home that is classed as the main living area than the CL group.

Table 3.6: Summary of key dwelling features (split by subsample)

Variable	Mean	SD	Min	Max
Full Sample (n=7,832)				
Number of floors	1.95	0.47	1	4
Year of Construction	1978.54	28.26	1753	2017
Percentage of home that is living area	21.02	9.55	0	81.1
Heatable Floor Area (m^2)	57.38	22.89	10.4	272.1
CL: Control (n=5,982)				
Number of floors	1.92	0.48	1	4
Year of Construction	1980.78	28.38	1753	2017
Percentage of home that is living area	21.68	10.03	0	81.1
Heatable Floor Area (m^2)	54.7	20.95	10.4	247.1
AT: Already Treated (n=1,279)				
Number of floors	2.03	0.42	1	4
Year of Construction	1969.5	27.47	1847	2008
Percentage of home that is living area	19.1	7.5	4.94	59.2
Heatable Floor Area (m^2)	65.81	26.05	16.9	212.3
TR: Treatment (n=571)				
Number of floors	2.07	0.44	1	3
Year of Construction	1975.32	24.03	1869	2006
Percentage of home that is living area	18.51	7.2	7.75	61.4
Heatable Floor Area (m^2)	66.53	27.43	13.5	272.1

Source: Author’s calculations based on SEAI BEH and EPC data. Note: Heatable floor variable reflects the floor area requiring heating, per SEAI. It is often not equal to the total floor area of a home.

3.5.3 Sample retrofit information

Table 3.7 details the average grant level and retrofit cost[24]. The average grant is lower for the TR group, with a larger average cost of works and a lower average number of measures. This suggests that more recent retrofits have not been influenced by the bonus subsidy for multiple measures. The three most common retrofits are an upgraded gas boiler with heating controls (36.28% AT, 50.61% TR), roof and cavity wall insulation (29.24% AT, 8.93% TR) and external wall insulation (14.54% in AT, 9.98% in TR), respectively.

Table 3.7: Uptake of Better Energy Homes subsidy

Total number of houses	**AT n=1,279**		**TR n=571**	
	Mean	**SD**	**Mean**	**SD**
Cost of Works (€)	4,307.81	4,075.15	4,784.04	5954.17
Grant Payable (€)	1,214.29	1,195.65	1,103.15	1058.79
Number of measures	1.48	0.58	1.22	0.47

Source: Author's calculations based on SEAI BEH data.

Table 3.8 illustrates how retrofits improve theoretical dwelling energy efficiency. It reports sample frequency for each EPC band, with Already Treated (AT) and Treatment (TR) houses moving from a pre-retrofit (column) to a post-retrofit (row) EPC. The most common change is from a D2 to C3 rating (n=117). This is followed by homes moving from D1 to C2 rating (n=114). Notably, no retrofitted house reaches A-rated status, and the majority that move to B-rated status climb from a D-rated house, at worst. This suggests that current retrofits help improve theoretical energy efficiency, but may not achieve policymaker ambition to retrofit all existing dwellings to B2 EPC standard (Government of Ireland 2019).

[24] Appendix 3.C features additional discussion of the sample and retrofit measures received.

Table 3.8: Full Sample change in categorical EPC (Count)

Pre-EPC	G	F	E2	E1	D2	D1	C3	C2	C1	B3	Control	Total
Post-EPC	**No.**	**No.**	**No.**	**No.**	**No.**	**No.**	**No.**	**No.**	**No.**	**No.**	**No.**	**No.**
G	2										227	229
F	10	2									308	320
E2	21	10									306	337
E1	32	28	14	4							386	464
D2	22	87	41	27	14						648	839
D1	18	57	89	67	80	18					776	1,105
C3	6	18	41	69	117	84	8				805	1,148
C2	11	6	7	38	98	114	88	20			880	1,262
C1	9	10	11	8	37	91	57	61	14		802	1,100
B3	9	11	7	7	12	14	27	33	30	5	458	613
B2	2	1	4	2	2	4	3	4	3		215	240
B1	2					1				1	100	104
A3											61	61
A2											10	10
Total	**144**	**230**	**214**	**222**	**360**	**326**	**183**	**118**	**47**	**6**	**5,982**	**7,832**

Source: Author's calculations. Note: Each column features the number of Already Treated (AT) and Treatment (TR) homes. Table 3.C.3 features a version of this table for the TR subsample.

3.5.4 Dependent variable: Actual energy use

Two adjustments are made to adapt the dependent variable of actual energy use to be comparable to the EPC (Equation 3.6). The first accounts for the ratio of primary to delivered energy. The EPC is based on primary energy use, including energy for generation and transmission. The second adjustment accounts for appliance usage, which does not factor into the EPC. SEAI (2018) suggests that appliance usage comprises, on average, 20% of home energy use. Two appliance usage (AA_j) measures are considered. The body of the paper applies a relative scaling of appliance usage ($AA_{Relative}$) to a factor of 80% (SEAI 2018). The actual energy use variable (EA_i) is measured in units of kilowatt-hours per bimonth.

$$EA_i = DeliveredEnergy_i * \frac{TotalPrimaryEnergy_i}{TotalDeliveredEnergy_i} * AA_j \qquad [3.6]$$

Direct comparison to the EPC requires actual energy use to be scaled by heatable floor area (kWh/m^2/year). The sample features 7,832 households with 15,664 observations of two full years (Y1, Y2) of meter readings.

Table 3.9 summarises the observations of annual actual energy use with the theoretical EPC. On average, actual energy use per square meter is lower than the theoretical level. Results in Section 3.6.3 use this variant of the EPC.

Table 3.9: Summary of mean annual Actual and Theoretical energy usage

Annual actual energy use	N	Mean	SD	Min	Max
Control (CL)	11,964	215	127	9.51	1,778
Already Treated (AT)	2,558	199	109	15.57	777
Treatment (TR)	1,142	207	116	11.2	873
Full Sample	**15,664**	**211**	**124**	**9.51**	**1,778**
Theoretical energy use	**7,832**	**233**	**96**	**40**	**1,241**

Note: Values in kWh/m^2/year. Actual energy use is adjusted for primary energy use and deflated for appliance use. 15,664 observations reflect two annual observations for every sample house (n=7,832): Control (CL, n=5,982 houses), Already Treated (AT, n=1,279 houses), Treatment (TR, n=571 houses).

3.6 Results

This section presents results based on the earlier research questions. The first result tests whether a retrofit lowers actual energy use and how this differs based on measures received (Section 6.1) The second result tests for differences between actual and theoretical energy use denoted by the EPC (6.2). The final result investigates the difference between expected and actual value for money in the upfront retrofit cost (6.3).

3.6.1 Result 1: Effect of receiving a retrofit on actual energy use

Following Fowlie et al. (2018), this section quantifies how actual energy use changes post-retrofit, using a binary retrofit variable for TR homes when a retrofit is received. Two fixed effects are considered: Household-level fixed effects account for unobserved heterogeneity within households over time. Time fixed effects account for period-specific effects that effect all houses equally. In all cases, standard errors are clustered at the household level.

Per Table 3.10, Model 1 shows a significant reduction in actual energy use post-retrofit (-130.867 kWh/bimonth). Model 2 highlights the influence of seasonality on energy use, as the retrofit coefficient changes to +118.721 kWh/bimonth with a time fixed effect.

Model 3 suggests that household-specific behaviour influences energy use, with an average fall in energy use of -811.449 kWh/bimonth post-retrofit. The preferred Model 4 accounts for both household-specific and period-specific heterogeneity, reporting an average fall in energy use of -157.175 kWh/bimonth post-retrofit. This equates to 943.05 kWh per annum.

Table 3.10: Impact of retrofit (TR subsample)

	Model 1	Model 2	Model 3	Model 4
Retrofit = 1	**-130.867*****	**118.721*****	**-811.449*****	**-157.173*****
	(34.806)	(34.196)	(52.047)	(50.425)
House FE	N	N	Y	Y
Time FE	N	Y	N	Y
Constant	1698.772***	2988.600***	1723.614***	2988.600***
N	(9.709)	(25.303)	(1.900)	(19.606)
R^2	125312	125312	125312	125312
Adj. R^2	0.000	0.220	0.259	0.475

Note: Table reports estimates of the change in bimonthly energy use following adoption of a retrofit. TR homes are classed as retrofit. The dependent variable is bimonthly electricity and gas energy use (in kWh). All specifications include standard errors (in brackets) clustered at the customer level (n=7,832). Asterisks indicate significance at the 10 percent (*), 5 percent (**), or 1 percent (***) level.

Although Model 4 helps to explain average retrofit-related savings, it does not account for different retrofit measures. Table 3.11 presents results for the eight retrofit measures (M_j), accounting for household and time fixed effects. Only retrofits with external wall insulation (-436.80 kWh/bimonth) or solar heating (-484.50 kWh/bimonth) are associated with significant reductions in actual energy use. This suggests that the average retrofit coefficient of -157.175 kWh/bimonth in Model 4 masks larger savings from specific measures.

Table 3.11: Impact of specific retrofit measures on average energy use

Model 5	M5.1	M5.2	M5.3	M5.4	M5.5	M5.6	M5.7	M5.8
Measure (Mj)	Cavity Wall	Dry-Lining	External Wall Insulation	Heat Controls (HC)	Gas Boiler w/HC	Oil Boiler w/HC	Roof Insulation	Solar Heating
Retrofit	50.525	510.686	**-436.8*****	-270.950	-117.19*	432.362	93.030	**-484.5*****
	(112.713)	(349.324)	(136.811)	(235.845)	(66.812)	(370.936)	(119.897)	(157.642)
House FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Constant	2988.6***	2988.6***	2988.6***	2988.6***	2988.6***	2988.6***	2988.6***	2988.6***
	(19.615)	(19.615)	(19.610)	(19.612)	(19.613)	(19.615)	(19.616)	(19.612)
N	125312	125312	125312	125312	125312	125312	125312	125312
# Adopted	95	16	70	27	319	7	116	23
R^2	0.475	0.475	0.475	0.475	0.475	0.475	0.475	0.475
Adj. R^2	0.440	0.440	0.440	0.440	0.440	0.440	0.440	0.440

Note: Each column reports estimates of the fall in bimonthly energy use following adoption of a specific retrofit measure for TR homes. The dependent variable is bimonthly electricity and gas energy use (in kWh). All specifications include standard errors (in brackets) clustered at the customer level (n=7,832). Asterisks indicate significance at the 10 percent(*), 5 percent(**), or 1 percent(***) level.

Most retrofits in the TR subsample receive one measure (n=458 of 571 households, 80.21%). A substantial number involve two (n=99, 17.34%) or three (n=14, 2.45%) measures. Table 3.12 presents results for 23 unique combinations of retrofit measures received, accounting for household and time fixed effects. Each model removes all observations from other TR retrofits, to focus on the difference between treated households in question, versus the CL and AT groups. This removes the potential for other retrofits to influence results.

Table 3.12 shows heterogeneity in the magnitude and direction of savings across retrofit combinations. Only 11 of the 23 combinations exert a significant effect after accounting for customer and time fixed effects. Six of the eleven measures deliver significant energy savings following the upgrade: Solar Heating (-503.2 kWh/bimonth), Oil Boiler w/HC + Solar Heating (-1,122), Gas Boiler (-171.15), Heating Controls + Solar Heating (-725.47), External Wall Insulation (-467.8) and External Wall Insulation + Gas Boiler w/HC (-725.6).

Table 3.12: Impact of specific combinations of retrofit measures

Model	Measures	Coef.	SE	Number of houses adopted
1	Solar Heating	**-503.2*****	**(168.554)**	**10**
2	Roof Insulation	-277.528	(227.462)	28
3	Oil Boiler w/ HC	**676.28*****	**(209.869)**	**5**
4	Oil Boiler w/HC; Solar Heating	**-1,122*****	**(8.291)**	**1**
5	Gas Boiler w/HC	**-171.15****	**(70.871)**	**279**
6	Gas Boiler w/HC; Solar Heating	-318.625	(322.727)	9
7	Gas Boiler w/HC; Roof Insulation	321.253	(357.239)	10
8	Heating Controls (HC)	-346.014	(245.812)	23
9	Heating Controls; Solar Heating	**-725.47****	**(291.883)**	**3**
10	External Wall Insulation	**-467.8*****	**(158.559)**	**53**
11	External Wall Insulation; Roof Insulation	-496.994	(358.637)	9
12	External Wall Insulation; Gas Boiler w/HC	**-725.6*****	**(260.932)**	**4**
13	External Wall Insulation; Gas Boiler w/HC; Roof Insulation	103.651	(570.225)	4
14	Internal Dry Lining	-158.522	(426.278)	3
15	Internal Dry Lining; Roof Insulation	-331.801	(741.139)	5
16	Internal Dry Lining; Gas Boiler w/HC	884.274	(589.127)	3
17	Internal Dry Lining; Gas Boiler w/HC; Roof Insulation	**1537.49*****	**(280.982)**	**4**
18	Internal Dry Lining; Heat Controls; Roof Insulation	**1787.64*****	**(11.149)**	**1**
19	Cavity Wall Insulation	-228.546*	(135.467)	37
20	Cavity Wall Insulation; Roof Insulation	187.476	(177.483)	51
21	Cavity Wall Insulation; Oil Boiler w/HC	**1,125.26*****	**(8.291)**	**1**
22	Cavity Wall Insulation; Gas Boiler w/HC	**702.947*****	**(267.524)**	**3**
23	Cavity Wall Insulation; Gas Boiler w/HC; Roof Insulation	228.735	(216.384)	3

Note: Coefficient reports the average change in bimonthly energy use (in kWh) after adopting a specific combination of retrofit measures for TR homes with an observed change (n=549 of a possible n=571). Model includes customer and bimonth fixed effects. Standard errors (in brackets) clustered at the customer level. Asterisks indicate significance at the 10 percent(*), 5 percent(**), or 1 percent(***) level.

Conversely, five combinations display a significant increase in energy use post-retrofit: Oil Boiler w/HC (676.28 kWh/bimonth), Internal Dry Lining + Gas Boiler w/HC + Roof Insulation (1537.49), Internal Dry Lining + Heat Controls + Roof Insulation (1787.64), Internal Dry Lining + Heat Controls + Roof Insulation (1787.64), Cavity Wall Insulation + Oil Boiler w/HC (1125.26) and Cavity Wall Insulation + Gas Boiler w/HC (702.947).

Results from Table 3.12 contradict Table 3.11, where only external wall insulation and solar heating featured a significant average reduction. In particular, upgrades that only feature a gas boiler upgrade now display a statistically significant average reduction in energy use (-171.15 kWh/bimonth). Although results are statistically significant, it is important to consider sample size, especially for oil boiler recipients, where actual energy use increases by +676.28 kWh/bimonth on average, yet a retrofit with an oil boiler and solar heating delivers average savings of -1,122 kWh per bimonth.

Results from Section 3.6.1 suggest that retrofits deliver savings in actual energy use. However, the magnitude of savings varies significantly by the measures installed, even leading to an increase in energy use. This highlights the vital role of occupant behaviour in determining energy use and the importance of accurately calibrating subsidy levels for specific measures. It bears repeating that results are based on the sample, which features relatively few cases of retrofit to the most efficient EPC levels (Table 3.8).

3.6.2 Result 2: Theoretical vs Actual energy use

It is important to verify that EPCs are accurate so that policies to improve dwelling energy efficiency translate to real savings. Table 3.13 performs a paired test for significant differences between actual (EA) and theoretical EPC-calculated energy use (ET) at the bimonthly frequency. The headline finding is that actual energy use is significantly below the theoretical level, with an average deficit of -23%.

The direction and magnitude of the effect differs when split by EPC grade. The most energy efficient homes display a surplus of actual energy use above theoretical, with an average surplus for homes from A2 (312%) to C1 (2.83%). Less energy efficient homes demonstrate an average deficit of actual energy use below theoretical, ranging from -6.76% for C2-rated homes to -63.48% for G-rated homes. This is consistent with research in other countries studying social housing (Majcen et al. 2013; van den Brom et al. 2018).

The extent to which actual energy use approximates the EPC differs by subsample. The largest deficit exists for TR houses (-28.12%), with the lowest deficit for AT dwellings (-21.64%). The AT average deficit is better than the CL average (22.96%), possibly reflecting improvements in AT homes.

The lack of major change post-retrofit for the TR subsample suggests that there is not an immediate narrowing of the deficit. Considered with the AT result, this presents evidence that occupant behaviour may take time to adjust.

Table 3.13: Test of significant difference between Actual and Theoretical energy use

	n	Mean EA	Mean ET	Difference	% Difference to ET	SE	P-Value
EA – ET	125,312	1,694	2,205	- 511	- 23.18	5	0***
EPC Grade							
A1	N/A	N/A	N/A	N/A	N/A	N/A	N/A
A2	160	2,454	594	1,860	312.84	131	0***
A3	976	1,543	679	864	127.32	54	0***
B1	1,649	1,511	923	588	63.68	36	0***
B2	3,796	1,639	1,255	384	30.57	25	0***
B3	9,401	1,690	1,482	209	14.09	17	0***
C1	16,936	1,647	1,602	45	2.83	12	0***
C2	19,679	1,700	1,833	- 133	- 7.25	12	0***
C3	18,224	1,682	2,001	- 319	- 15.93	12	0***
D1	17,941	1,695	2,262	- 567	- 25.07	13	0***
D2	13,689	1,723	2,590	- 867	- 33.48	16	0***
E1	7,647	1,661	2,840	- 1,179	- 41.51	21	0***
E2	5,772	1,868	3,253	- 1,385	- 42.58	27	0***
F	5,587	1,677	3,614	- 1,937	- 53.60	28	0***
G	3,855	1,794	4,921	- 3,127	- 63.54	44	0***
Dwelling Type							
Apartment	9,536	1,260	1,926	- 666	- 34.58	15	0***
Detached	15,264	2,140	3,247	- 1,108	- 34.11	21	0***
Semi-detached	45,648	1,792	2,375	- 583	- 24.54	9	0***
Terrace	54,864	1,564	1,822	- 259	- 14.19	7	0***
Subsample							
Already Treated	20,464	1,816	2,318	- 501	- 21.64	13	0***
Control	95,712	1,648	2,139	- 491	- 22.96	6	0***
Treatment	9,136	1,899	2,641	- 743	- 28.12	23	0***
TR Pre-Retrofit	4,562	2,230	3,090	- 860	- 27.83	37	0***
TR Post-Retrofit	4,574	1,568	2,194	- 626	- 28.53	26	0***

***** P<0.01, **P<0.05, *P<0.10. Note: Observations at bimonthly frequency. Variable of actual energy use features a 20% deflation to account for appliance use ($AA_{Relative}$). 125,312 bimonthly observations for 7,832 households. Values in terms of kWh/m2/year. EPC for TR households is pre-retrofit EPC prior to retrofit and post-retrofit EPC grade from the date of retrofit onwards.**

Results in Section 3.6.2 suggest that people do not behave according to their EPC, with differences most pronounced at opposite ends of the EPC spectrum. This result is not unexpected, as model measurement error often exists (Allcott and Greenstone 2012).

Policies to subsidize domestic retrofit to attain a high national EPC standard (Government of Ireland 2019) may lead to unintended consequences, such as households increase their energy use after availing of a subsidised home energy retrofit. However, this concept of rebound is well-established in the literature (Heesen and Madlener 2018; Sorrell et al. 2009; Sunikka-blank and Galvin 2012) and improving the comfort and wellbeing of occupants is likely part of the motivation behind offering the subsidy, in particular to socially vulnerable groups (Coyne et al. 2018). From the perspective of reducing energy demand, such a result in the Irish context would hinder efforts towards meeting national and EU-level targets.

3.6.3 Result 3: Value for money

Collins & Curtis (2017) investigated the value for money of specific retrofits through the Better Energy Homes grant using theoretical changes in energy use. However, Section 3.6.2 shows how actual energy use deviates from the theoretical level. This section innovates on earlier work by studying actual changes in energy use. Equation 3.7 defines expected value for money (eVFM) for the household (i) as the ratio of the difference in the capital cost (C_0) net of the level of grant received (G_0) to the change in the EPC (kWh/m^2/year) before and following retrofit. A high eVFM suggests there is either a large upgrade cost (numerator) or a small change in theoretical energy efficiency (the denominator).

$$eVFM_i = \frac{C_0 - G_0}{EPC_{PreRet} - EPC_{PostRet}} \qquad [3.7]$$

eVFM is limited because it does not reflect differences between actual and theoretical energy use. Equation 3.8 presents actual value for money (aVFM) that scales eVFM by delta (δ), a weight reflecting the average difference between bimonthly actual and theoretical energy use by EPC grade (Section 3.6.2) [25].

[25] $\boldsymbol{\delta}$ does not change for AT homes. For TR homes, $\boldsymbol{\delta}$ reflects the average difference between actual and theoretical energy use for the pre-retrofit and post-retrofit EPC, as appropriate. Appendix 3.D considers a separate measure of aVFM for 166 retrofits, with one full year of energy use before and after retrofit.

$$\delta_i = \frac{\overline{(EA_{PreRet,s,t} - ET_{PreRet,s,t})} + \overline{(EA_{PostRet,s,t} - ET_{PostRet,s,t})}}{2}$$

[3.8]

$$aVFM_i = \frac{C_0 - G_0}{EPC_{PreRet} - EPC_{PostRet}} * (1 + \bar{\delta})$$

Table 3.14 presents VFM analysis for both the AT and TR subsamples. The top panel summarizes the pre- and post-retrofit EPC (in units of kWh/m^2/year), the average cost of works and grant value. Compared to the AT group, the TR subsample features slightly better theoretical energy efficiency, costlier retrofits and lower grant amounts.

The bottom panel of Table 3.14 compares expected and actual VFM. For AT households, average aVFM (36.52 €/kWh/m^2/year) is lower than average eVFM (43.83 €/kWh/m^2/year). This suggests that it costs less to improve actual energy efficiency than improving theoretical energy efficiency. The effect is stronger for TR households, where average aVFM (43.60 €/kWh/m^2/year) is lower than average eVFM (56.25 €/kWh/m^2/year). Valuations based on actual energy use show a larger reduction for TR houses, with an average drop of 12.65 €/kWh/m^2/year, compared to a drop of 7.31 €/kWh/m^2/year for AT households.

Table 3.14: Expected value for money (eVFM) and actual value for money (aVFM)

	AT households (n=1,277)				***TR households (n=571)***			
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Dwelling Characteristics								
Pre-Retrofit EPC	312.92	106.63	139.86	1,311.66	296.22	94.8	128.39	847.08
Post-Retrofit EPC	216.29	54.33	83.42	518.73	204.88	52.96	86.14	449.03
Cost of works (€)	4,307.81	4,075.16	460	29,700	4,784.04	5,954.17	300	100,000
Grant value (€)	1,214.29	1,195.65	250	5,560	1,103.15	1,058.79	300	5,800
Delta δ (%)	-0.19	0.17	-0.6	0.45	-0.25	0.1	-0.57	-0.07
***Household VFM* (€/kWh/m^2/year)**								
eVFM	43.83	72.55	-122.7	1,451.22	56.25	85.09	0	1,041.08
aVFM	36.52	56.39	-79.71	807.27	43.60	69.95	0	877.42
Difference	-7.31	24.48	-730.7	42.98	-12.65	18.22	-244.6	0

Note: Table reports the average expected value for money of receiving a retrofit for 1,277 AT households and 571 TR households. Pre-Retrofit EPC and Post-Retrofit EPC are in units of kWh/m^2/year.

Results in Section 3.6.3 suggest that the upfront cost of retrofit is lower when factoring in the difference between actual and theoretical energy use. This suggests that there would be wider retrofit adoption if customers understood this difference. This may help explain why adoption of certain energy efficiency technologies may be limited (Jaffe and Stavins 1994a).

3.7 Concluding remarks

Evidence on the effectiveness of retrofit schemes note that although subsidies could improve societal welfare, they currently do not represent value for money or deliver the savings expected (Allcott and Greenstone 2017; Fowlie et al. 2018). The effectiveness of subsidised retrofit policies is important for countries that must achieve energy savings from the residential sector. This paper is one of the largest studies of retrofit using measured whole-home energy use data for a non-social housing sample. It compares the 'treatment' of a subsidized retrofit with two important control groups: Homes that received a subsidized retrofit before the observation period and homes that do not receive a subsidized retrofit during the observation period.

The first result suggests that a retrofit reduces actual energy use by -157.173 kWh/bimonth on average, controlling for household and time fixed effects. When considering every combination of measures, six combinations deliver energy savings, while five are associated with increased energy use. Notably, gas boiler upgrades show a significant average reduction in energy use (-171.15 kWh/bimonth). From a policy perspective, this shows how retrofit is effective in many cases and subsidy levels should be calibrated accordingly. Results suggest that subsidies for gas boiler replacement and external wall insulation should be promoted, with resources diverted from ineffective measures. Further investigation is warranted, as the subsidy may be designed to improve other outcomes (Ryan and Campbell 2012).

On this issue, the Irish government has outlined plans to consider how retrofits could be designed in a more affordable manner. In particular, by designing the policy so the cost of the upgrade is recouped through household bills over time, rather than the entire cost being levied prior to the upgrade (Government of Ireland 2019) . Furthermore, SEAI are conducting a National Heat Study in 2021 that outlines potential options for reducing heating emissions in Ireland on the pathway towards a net-zero emissions economy by 2050[26].

[26] See https://www.seai.ie/data-and-insights/national-heat-study/

The second result finds significant differences in actual and theoretical energy use, with an average deficit of 23.18% translating to an average annual deficit of 3,066 kWh/year. The direction and magnitude of this difference varies by the EPC level, with the most energy efficient households displaying a surplus and the least energy efficient households exhibiting a deficit. The difference varies by subsample, with AT homes featuring the smallest average deficit (-21.64%) and TR homes featuring the largest deficit (-28.12%). This possibly reflects the improved efficiency of AT homes. This highlights the importance of studying actual energy use data, instead of relying purely on asset rating models that inform EPCs.

The third result measures value for money. Using changes in the EPC, the average expected value for money of a retrofit is 47.81 €/kWh/m^2/year. This has risen for more recent TR households (56.25 €/kWh/m^2/year) compared to earlier AT houses (44.03 €/kWh/m^2/year). A measure of actual value for money is constructed, reflecting EPC-level differences in actual and theoretical energy use. The average for the AT group is 36.52 €/kWh/m^2/year, lower than the TR average (43.60 €/kWh/m^2/year). This suggests that retrofits represent more value than advertised by EPC-based measures. From a policy perspective, measuring actual energy use could present a more accurate guide to homeowners on the effective cost of retrofit. National plans to install smart meters in homes by 2024 should help provide a comprehensive view of residential energy use (Government of Ireland 2019).

There are some limitations of the study. In particular, the sample focuses exclusively on gas-heated homes from the largest utility. Further cooperation from every utility in the market could study more houses and reduce sample attrition due to customer switching. Secondly, the data lacks tariffs and socioeconomic information of occupants. Finally, this work does not include other benefits that accrue from having a more efficient home, including emissions saved, improved health and comfort. The focus in this study is on how policies and models should be revised to reflect actual patterns of consumer energy use.

Taken together, the first result shows retrofits reduce energy use. However, the second result shows how occupants with a better EPC are more prone to consuming above the EPC-predicted level. There is concern that subsidising retrofit will lead to more efficient homes, but consume more energy at those EPC levels, This work sounds a note of caution regarding possible unintended consequences of extensive retrofit, including potential for occupants to change their behaviour to the detriment of national emissions reduction targets.

3.A Additional details of BEH subsidy

Table 3.15 highlights past values of the BEH scheme. This may only be relevant for homes in the 'Already Treated' group since almost every home in our 'Treatment' sample receives a retrofit in the period following March 2015. Since then, there has been no change in the grant levels. Grant measures include insulation, replacement of an inefficient boiler or an upgrade to include solar heating. Comprehensive (or 'deep') retrofits within the Irish Climate Action Plan, focus on significantly upgrading dwelling energy efficiency (Government of Ireland, 2019). However, the estimated €50 billion exchequer cost of a nationwide retrofit scheme has led to additional suggestions, including a transition away from subsidies towards financing where the capital cost is reclaimed through energy bill savings.

Table 3.15: [3A] Full schedule of Better Energy Homes grant payment levels

		Grant value (€)				
Measure	**Category**	**March 2009**	**June 2010**	**May 2011**	**December 2011**	**March 2015**
Roof	Attic Insulation	250	250	200	200	300
Wall	Cavity wall insulation	400	400	320	250	300
	Internal dry-lining[1]	2500	2500	2000	900/1350/1800	1200/1800/2400
	External wall insulation[1]	4000	4000	4000	1800/2700/3600	2250/3400/4500
Boiler	High efficiency boiler (oil / gas) with heating controls	700	700	560	560	700
	Heating controls upgrade only	500	500	400	400	600
Solar	Solar heating			800	800	1200
BER	Mandatory Pre- and Post-Retrofit Audit	100	100	80	50	50
Bonus	Three measures					300
	Four measures					100

Source: Collins & Curtis (2016). Note: [1] Values for Apartment / Semi-Detached / Detached houses, respectively where split.

3.B Construction and cleaning of meter readings

This appendix summarises the steps taken to link, clean and filter the sample of residential energy use to reach a sample that is suitable for analysis.

3. Linking customers

- Gas fuelled homes are identified by linking Electric Ireland gas customer accounts with the corresponding Electric Ireland electricity account.
- Electricity accounts are anonymously merged with the SEAI dwelling data using the electric meter number (MPRN), which was unobservable to the research team.
- There are 286,523 unique customer matches between the original Electric Ireland measured energy use data and the SEAI dwelling data. Of this, 21,198 are unique matches for a gas customer account that is linked to an electricity customer account.

4. Energy data merge and sample restrictions

The original energy dataset features 30,045,696 daily energy readings (28,563,625 electricity, 1,482,071 gas) beginning November 2011. We drop households with no match in the SEAI dwelling data. Readings are aggregated bimonthly and adjusted to reflect the period of use e.g. A reading in March 2015 reflects usage in January 2015. Additional observations are dropped for the following reasons:

- Total household metered energy usage is zero.
- House is not heated by gas (per SEAI).
- Multiple meters for a house (per SEAI).
- A house received a grant-supported retrofit during the observed period (per SEAI).
- Drop electricity readings before the start of the gas sample (November 2014) to focus on the common period of electricity and gas use.
- A ratio of the number of missing periods to the number of periods present is created. This ratio is equal to 0.75 if a household is present for 16 periods but if missing for any four periods. Any household with a ratio less than 0.5 is dropped, which does not discriminate against homes that enter the data later.

- Drop any household with a gap between observations of at least six months. Although the customer might be present during the entire sample period, such a large missing period makes it unsuitable for analysis, especially for annual values.
- Drop any house with fewer than six observations (a full year of readings).
- Drop any house with an annual energy usage value (Y1, Y2) reading in the top or bottom one percent of the distribution to observe households with realistic energy use.
- Drop homes with an SEAI heatable floor area of less than $10m^2$. Mostly apartments.

Remove households with a Delivered Energy value in the top or bottom 1% of the distribution. As noted in Appendix 3.A, the SEAI dataset includes two variables of calculated annual use, one reflecting consumed energy (Delivered Energy) and the other including an overhead for energy generation (Primary Energy).

3.C Extended description of sample dwelling characteristics

Table 3.16 details the combination of retrofit measures received. For both the AT and TR groups, the top three retrofit combinations are similar. For the sample, the most common measure is an upgraded gas boiler with heating controls (36.28% AT, 50.61% TR). The next two most popular combinations are roof and cavity wall insulation (29.24% AT, 8.93% TR) and external wall insulation (14.54% in AT, 9.98% in TR), respectively.

Table 3.16: [3B] Better Energy Homes grant measures received

Measures	All n	All %	AT n	AT %	TR n	TR %
Gas boiler with HC	753	40.7	464	36.28	289	50.61
Roof Insulation + Cavity Wall Insulation	425	22.97	374	29.24	51	8.93
External Wall Insulation	243	13.14	186	14.54	57	9.98
Roof Insulation + Gas Boiler w/HC	65	3.51	54	4.22	11	1.93
Heating Controls (HC)	54	2.92	29	2.27	25	4.38
Cavity Wall Insulation	37	2			37	6.48
Roof Insulation + External Wall Insulation	31	1.68	22	1.72	9	1.58
Roof Insulation	30	1.62	1	0.08	29	5.08
Solar Heating	30	1.62	17	1.33	13	2.28
Roof Insulation + Gas Boiler w/ HC + Internal Dry Lining Insulation	28	1.51	24	1.88	4	0.7
Roof Insulation + Internal Dry Lining Insulation	27	1.46	22	1.72	5	0.88
Gas Boiler w/ HC + External Wall Insulation	17	0.92	13	1.02	4	0.7
Internal Dry Lining Insulation	14	0.76	11	0.86	3	0.53
Oil Boiler w/ HC	14	0.76	9	0.7	5	0.88
Solar Heating + Gas Boiler w/ HC	14	0.76	5	0.39	9	1.58
Roof Insulation + Gas Boiler w/ HC + Cavity Wall Insulation	11	0.59	8	0.63	3	0.53
Roof Insulation + Heating Controls (HC)	9	0.49	9	0.7		
Roof Insulation + Gas Boiler + External Wall Insulation	8	0.43	3	0.23	5	0.88
Gas Boiler w/ HC + Internal Dry Lining Insulation	7	0.38	4	0.31	3	0.53
Roof Insulation + Heating Controls (HC) + Internal Dry Lining Insulation	7	0.38	6	0.47	1	0.18
Gas Boiler w/HC + Cavity Wall Insulation	5	0.27	2	0.16	3	0.53
Roof Insulation + Heating Controls (HC) + Cavity Wall Insulation	4	0.22	4	0.31		
Solar Heating + Heating Controls (HC)	4	0.22	1	0.08	3	0.53
Roof Insulation + Oil Boiler w/ HC	2	0.11	2	0.16		
Roof Insulation + Oil Boiler w/ HC + Cavity Wall Insulation	2	0.11	1	0.08	1	0.18
Solar Heating + Oil Boiler w/ HC	2	0.11	1	0.08	1	0.18
Solar Heating + Roof Insulation	2	0.11	2	0.16		
Solar Heating + Roof Insulation + Gas Boiler w/HC + External Wall Insulation	2	0.11	2	0.16		
Heating Controls (HC) + Internal Dry Lining Insulation	1	0.05	1	0.08		
Heating Controls (HC) + External Wall Insulation	1	0.05	1	0.08		
Roof Insulation + Heating Controls (HC) + External Wall Insulation	1	0.05	1	0.08		
Total Number of Households	**1,850**	**100**	**1,279**	**100**	**571**	**100**

Note: Table reflects the all retrofits observed in the sample (n=1,850). Values are in descending order of retrofit measure combinations for both the Already Treated (AT) and Treatment (TR) subsamples.

Households are linked with bimonthly weather information with the nearest of seven weather stations (Table 3.17). A bimonthly Heating Degree Day variable reflects the number of days where mean temperature is below 15.5 degrees Celsius and total rainfall variable is also included. Later results omit these variables due to collinearity with the bimonthly frequency.

Table 3.17: [3C] Summary of weather controls

Variable	Mean	SD	Min	Max
Bimonthly heating degree days	53.55	11.09	20.1	60.9
Total bimonthly rainfall (mm)	163.72	69.9	97.6	368.4

Source: European Climate Assessment & Dataset **http://eca.knmi.nl/dailydata/customquery.php**

Table 3.18 summarises the changes in the EPC, split by subsample. The average reduction in theoretical energy use is 30 per cent, falling from 307.77 kWh/m^2/year to 232.74 kWh/m^2/year. It is notable that a retrofit improves theoretical dwelling energy efficiency to the point that the average retrofit home (TR and AT) is more efficient that the average Control (CL) home.

There is a similar reduction in theoretical energy use for Already Treated (AT) and Treatment (TR) subsamples (-96.63 kWh/m^2/year for AT compared to -91.35 kWh/m^2/year for TR). Before retrofit, AT homes are slightly less efficient (312.92 kWh/m^2/year, E1 EPC average) than TR homes (296.22 kWh/m^2/year, D2 EPC average). One likely explanation for this difference is the average year of construction (Table A3.4), which is 1969 for the AT group and 1975 for the TR group. After the retrofit, the same trend continues, with AT homes being slightly less energy efficient (216.29 kWh/m2/year, C3 average) than TR homes (204.88 kWh/m^2/year, C3 average), yet within the same EPC band.

Table 3.18: [3D] Change in EPC-calculated annual energy use

Variable	Mean	Std. Dev	Min	Max
Full Sample (n=7,832)				
Post-retrofit EPC	6.84	2.54	1	14
Pre-retrofit EPC	4.65	2.11	1	10
Difference	2.58	1.64	0	11
Post-retrofit theoretical energy use	232.74	95.74	40	1240.7
Pre-retrofit theoretical energy use	307.77	103.38	128.4	1311.7
Difference	-95	83.19	-1014.2	12.1
Control (n=5,982)				
Post-retrofit EPC	6.72	2.71	1	14
Pre-retrofit EPC				
Difference				
Post-retrofit theoretical energy use	238.92	104.56	40	1240.7
Pre-retrofit theoretical energy use				
Difference				
Already Treated (n=1,279)				
Post-retrofit EPC	7.11	1.8	1	12
Pre-retrofit EPC	4.54	2.09	1	10
Difference	2.57	1.63	0	11
Post-retrofit theoretical energy use	216.29	54.33	83.4	518.7
Pre-retrofit theoretical energy use	312.92	106.63	139.9	1311.7
Difference	-96.63	86.38	-1014.2	12.1
Treatment (n=571)				
Post-retrofit EPC	7.5	1.8	2	12
Pre-retrofit EPC	4.89	2.14	1	10
Difference	2.61	1.67	0	11
Post-retrofit theoretical energy use	204.88	52.96	86.1	449
Pre-retrofit theoretical energy use	296.22	94.8	128.4	847.1
Difference	-91.35	75.52	-665.9	-4.96

Note: Theoretical energy use is in units of kWh/m^2/year. This informs the EPC, which ranges from 1 to 15 in ascending theoretical energy efficiency. Two AT households experienced a rise in theoretical annual energy use but remained within the same EPC category.

3.D Alternative value for money (VfM) subsample (n=166)

Section 3.6.3 studies the value for money for specific retrofit combinations. In particular, it distinguishes between the expected value for money in the change in EPC and the actual value for money by multiplying the expected change in EPC with the average deficit or surplus between actual and theoretical energy use observed in Section 3.6.2. This is to facilitate a comparison between all households. This appendix features a separate value for money analysis for a subsample of 166 retrofits that occur in the middle of the observation period, with one full year of energy use before and after retrofit. Equation 3.D.1 denotes a VFM measure that replaces the change in the EPC with the change in actual energy use.

In this study, energy use is observed from November 2014 to June 2017. Actual value for money (aVFM) can be compared for a subset of 166 retrofits that occur in the middle of the sample (from November 2015 to June 2016), where a full year of pre-upgrade (November 2014 - October 2015) and a full year of post-upgrade (July 2016 - June 2017) energy readings are available. For this subsample, it is possible to compare the expected (eVFM) and actual (aVFM) value for money (assuming that both years feature similar weather).

$$aVFM_{HH} = \frac{C_0 - G_0}{EA_{PreRet} - EA_{PostRet}} \qquad [3.D.1]$$

Table 3.19 compares the expected and actual VFM for the subsample (n=166). For households, the average expected VFM (56.13 €/kWh/m^2/year) is higher than actual VFM (23.72 €/kWh/m^2/year). This suggests that it is cheaper to improve actual energy efficiency (based on the change in two years of energy readings) than improving theoretical energy efficiency (denoted by the change in EPC). A similar result holds for the policymaker measure, where the actual VFM improves when it is based on changes in actual energy use.

Generalised to the population, it suggests that the upfront value of a retrofit is actually higher, so there should be less of a barrier to engaging with energy efficiency improvements. However, one limitation of the actual VFM metrics is the fact that they are based on changes in actual energy use, so higher energy use post-retrofit creates a negative VFM.

Table 3.19: [3E] Value for Money (VfM) comparison

Suitable TR households (n=166)	Unit	Mean	SD	Min	Max
Pre-Retrofit EPC	$kWh/m^2/year$	283.52	91.51	146.51	847.08
Post-Retrofit EPC	$kWh/m^2/year$	199.78	49.41	115.34	449.03
Pre-Retrofit actual energy use	$kWh/m^2/year$	197.95	115.04	13.62	552.76
Post-Retrofit actual energy use	$kWh/m^2/year$	123.35	61.25	18.99	346.83
Household VFM					
eVFM	€/$kWh/m^2/year$	56.13	63.35	1.5	453.11
aVFM	€/$kWh/m^2/year$	23.72	378.11	-1828.67	4207.75
Difference	€/$kWh/m^2/year$	32.41	384.52	-4166.77	1933.84

Note: Table reports the average expected value for money of receiving a retrofit for a subset of 166 TR households that receive a retrofit in the middle of the observation period, following Equation 3.E.1.

Section 3.6.2 noted that actual energy use differs from the theoretical level. Results in Appendix 3.D completes this line of inquiry by highlighting how the value for money also changes when considering changes in actual energy use for a subsample. Although results are based on a sample of various retrofits, they suggest that retrofits, on average, offer better value for money than expected. This emphasises the importance of accurate EPC modelling.

Chapter 4: A Model of Technology Diffusion to Forecast Data Centre Electricity Use

4.1 Introduction

Most economic agents struggle to predict the future. This makes it difficult for policymakers to be proactive and forward-looking in their design of regulations and price controls. A classic example of this concept is how few could have predicted how reliant the modern economy would become on the internet as an engine for economic growth. However, the European Commission now considers internet infrastructure “a key new type of economic asset” (European Commission 2017a, 2017b), the UN lists affordable internet access as a Sustainable Development Goal (UN 2015) and it is estimated that four billion people are currently without internet access (World Economic Forum 2016).

The policy ambition behind increasing internet access is justified. Pradhan et al. (2013) found evidence of a long run relationship between the percentage of a country’s population with internet connectivity and economic growth, inflation and government expenditure for OECD countries during the period 1990 to 2010. Koutroumpis (2009) found a significant causal impact of increased broadband penetration on economic growth for OECD countries. In the United States, the adoption of internet is associated with increased economic activity, higher income growth and lower unemployment growth in rural areas (Whitacre et al. 2014). Lechman and Kaur (2016) suggest a link between increasing internet connectivity, ICT use and improved social progress in developing countries from 2000 to 2014.

Internet infrastructure is a complex network that requires significant investment and running costs. Data centres form the beating heart of modern internet infrastructure, and their significant energy footprint, private ownership and (relatively) rapid growth presents a challenge to policymakers. This paper demonstrates how an epidemic model of technology diffusion can forecast the potential energy savings that data centres could deliver energy use, were they to adopt a specific energy efficiency technology (EET).

Data centres are large industrial units dedicated to storing and transmitting electronic data. They help facilitate innovations such as cloud computing (McKendrick 2016), online transactions, social media (McKinsey 2010) and driverless cars (Macauley 2016).

The volume of data in the economy is expected to grow rapidly in the coming years, with estimates that global annual internet traffic will be 3.3ZB in 2021 (zettabyte, or one trillion gigabytes), almost triple the 2016 level of 1.2ZB (CISCO 2017). International Data Corporation estimates that the 'digital universe' of data will grow from 4.4ZB in 2013 to 44ZB in 2020 – more than doubling every two years[27].

Estimates vary on the energy footprint of the data centre sector. Recent estimates suggest that data centres account for one per cent of global electricity demand (Masanet et al. 2020). In the EU, data centres were estimated to consume 78 TWh of electricity in 2015, 2.5% of total electricity use (European Commission 2015). Koomey (2011) estimates that global data centre electricity consumption doubled from 2000 to 2005 and increased by 56% from 2005 to 2010[28]. Ebrahimi et al. (2014) estimate that US data centres consume between 1.3% to 2% of the US national electricity consumption. In a study of equipment shipment data, Shehabi et al. (2018) forecast 2020 US data centre electricity use around 70 billion kWh, noting how energy efficiency has prevented electricity use from rising proportionally with the exponential increase in data. Importantly, this relationship is contingent on the nature and diffusion of future energy efficiency technologies (Shehabi et al. 2018).

For information-intensive firms, the data centre can represent half of the company's corporate carbon footprint (McKinsey 2010). Appendix 4.A provides a technical overview of common data centre cooling techniques. However, firms often fail to optimize data centre energy efficiency. The Uptime Institute estimate that 20% of the servers in a data centre are underutilised, with 'comatose servers' that idle on standby. Koomey and Taylor (2015) found that 30% of servers (from a sample of 4,000 across North America) delivered no computing services in the six months prior to monitoring. A subsequent study found that a quarter of comatose servers were located in firms that took no action to remove them (J. Koomey and Taylor 2017).

Accurately reporting plant-level efficiency is difficult. The most popular metric is Power Usage Effectiveness (PUE), which is the ratio of total data centre energy use divided by the energy for computing equipment.

[27] See https://www.emc.com/leadership/digital-universe/2014iview/executive-summary.htm
[28] Analysis based on commercial sales of server components, omits the largest 'hyper scale' facilities.

In a 2014 Uptime Institute survey of 1000 data centre managers, the average PUE is 1.7[29]. Brady et al. (2013) find that firms manipulate PUE by including energy consumption that is not strictly for IT purposes. PUE also fails to account for hardware efficiency, energy productivity and environmental performance (Horner and Azevedo 2016). Ebrahimi et al. (2014) note that rising energy costs are likely to spur adoption of more energy efficient technologies.

This paper applies an epidemic model of technology diffusion to forecast how potential efficiencies in data centre energy use could be adopted over time. It is motivated in large part by the rapid rise in data centre energy use. The method applied in this paper can be applied to any existing or emerging data centre cooling technology. The specific innovation considered in this study is a switch to direct liquid server cooling, which addresses a number of challenges by rising server power density: Liquid cooling has a higher thermal carrying capacity than air cooling, it can be fitted to existing server units and can halve the floor space required (Sickinger et al. 2014). Furthermore, liquid cooling could help data centres serve as a source of low-carbon waste heat supply to the grid (Ebrahimi et al. 2014).

As noted by Garimella et al. (2013), liquid cooling could reduce total data centre electricity demand by a third. After quantifying the rate of technology adoption, it models the reduction in electricity use and associated CO_2 emissions. This is the first study to use an epidemic model of technology diffusion in the context of the data centre sector. It serves as a helpful resource for researchers that are dealing with the need to provide sectoral forecasts under uncertainty with little detailed information. This is studied for Ireland, a key hub for global ICT activity where data centres are expected to be responsible for between 28% to 37% of national electricity demand by 2028, depending on the level of construction (EirGrid, 2019).

The rest of the chapter is laid out as follows: Section 4.2 provides context to the Irish data centre and national energy picture. Section 4.3 details the conceptual framework, model of technology diffusion, assumptions, data and scenarios considered. Section 4.4 details the results for electricity demand and emissions. Section 4.5 concludes.

[29] See https://journal.uptimeinstitute.com/2014-data-centre-industry-survey/

4.2 Case study system

The previous section detailed how data centres have become an important part of the global economy and its energy use. This section focuses on the Irish economy, its complex relationship with data centres and the potential implications this has for the Irish energy market and related climate change targets.

4.2.1 The Irish data economy

Ireland is responsible for 14% of the global trade in ICT services in 2016 ($70 billion), higher than any other country (OECD, 2017). It is the second-largest European city in terms of data centre capacity, trailing London (Host in Ireland, 2017). More recent publications note that Dublin accounts for a quarter of the European data centre market with over 53 data centres (Host in Ireland, 2019). Ireland features the key infrastructure to support data centres including a secure electricity supply and technological readiness (Schwab, 2015). The data centre location decision is influenced by quality electricity supply, robust fibre broadband infrastructure and the presence of affordable business units (IWEA 2015).

Despite the large energy footprint of the data centre sector on a constrained island electricity network, sectoral growth is anticipated to continue due to the strong economic benefits. The Irish Development Agency surveyed a sample of 16 data centre managers and estimated that since 2010, the data centre sector has contributed €7.13bn to the Irish economy (IDA 2018). The benefit is split into €4.64bn in construction (of which €1.59bn is indirect) and €2.49bn in operational expenditures (of which €0.90bn is also indirect). In response to concerns about the relatively low level of direct employment by data centres (Lillington 2016), IDA (2018) notes that annual average employment from data centres is equivalent to 5,700 full-time equivalent employees. Furthermore, they note that companies with a data centre in Ireland have increased their employment from 4,000 to almost 10,000 since 2010.

The Irish government views data centres as essential for becoming a pillar of the European digital economy (Government of Ireland 2018). It aims to implement a plan-led approach that recognises the significant electricity demand of data centres. It aims promote regional data centre investment that avoids unnecessary grid infrastructure investment.

It also plans to balance the distributional impact of higher energy costs from an increase in data centre capacity. It also aims to streamline data centre planning processes. If achieved, these plans could foster data centre growth with minimal disruption.

Firms note how an Irish data centre justifies further investment in finance, sales and software engineering in Ireland. This has led to collaboration between firms and higher-level education institutes to develop skills. The Irish market features spatial agglomeration, where companies build data centres in proximity to large data service providers to benefit from lower connection latency (IDA, 2018). Recent changes in legislation could shift demand for Irish data centres. The introduction of General Data Protection Regulation (European Union 2016) has important consequences for how companies handle EU consumer data (EU GDPR 2017). Paired with the looming exit of Britain from the European Union, it is likely that UK-based firms might need to relocate their data to comply with data protection legislation.

4.2.2 Challenges facing the Irish energy market

The popularity of Ireland as a data centre destination poses challenges for the electricity grid. Businesses seeking a connection capacity of less than 20MVA connect to the grid through ESB Networks, the Distribution System Operator (DSO) of the medium-to-low voltage power lines. The increasing capacity of data centres above this threshold requires direct applications to EirGrid, the transmission system operator (TSO) of high-to-medium voltage power lines. Through this channel, it is possible for private negotiation with the TSO throughout the application and connection process[30]. EirGrid estimates that approximately 490 MVA installed capacity of data centres in 2019 consumes roughly 13.9% of the national electricity demand (~4.3 TWh out of 30.9 TWh). By 2028, it is expected that data centres could be responsible for between 28% to 37% of national electricity demand, depending on the level of growth (EirGrid 2019). New data centre capacity is expected to drive three quarters of the national growth in electricity demand over the next decade (Oireachtas 2017).

Figure 4.1 illustrates how national electricity demand forecasts (top panel) are influenced by expected data centre capacity (bottom panel) across three demand scenarios:

[30] See https://www.eirgridgroup.com/customer-and-industry/becoming-a-customer/demand-customer/

- Low: All existing data centre capacity and half of all in-progress enquiries
- Medium: All existing data centre capacity and all in-progress enquiries
- High: All existing, in-progress and likely material enquiries

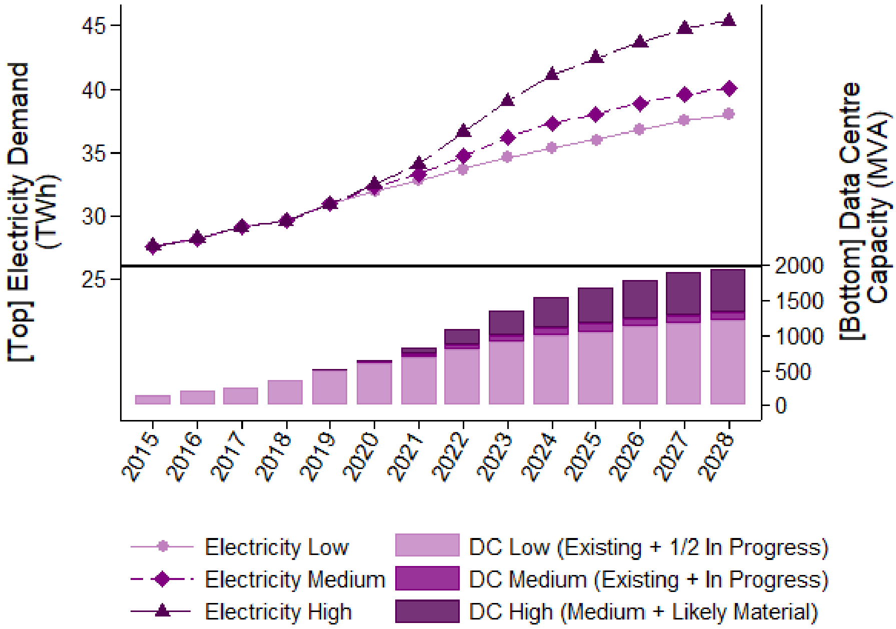


Figure 4.1: EirGrid (2019) Forecast of Electricity Demand and Data Centre Capacity

The EU has set targets to achieve climate neutrality by 2050 (European Commission 2019a). Earlier 2030 climate targets include i) sourcing 32% of the energy mix from renewable sources, ii) reducing GHG emissions by 40% from 1990 levels and iii) a 32.5% improvement in energy efficiency, relative to a 2007 forecast of 2030 energy use (European Parliament 2018). Ireland aimed to improve energy efficiency by 20% before 2020 relative to average national energy use from the period 2001-2005, equivalent to savings of 31,925 GWh (DCENR 2009). By early 2017 Ireland has only achieved a 12% improvement in energy efficiency and is expected to miss the 2020 target by 3.77% (DCCAE 2017a), with compliance for the 2020 target potentially costing €80-140 million (Deane 2017).

In recent years, Ireland has become a home to a thriving data centre industry. At the same time, Ireland is not on track to meet current EU emissions reduction targets. Although data centres have many associated economic benefits, future sectoral growth has the potential to undermine progress towards reducing energy use and emissions in future targets.

4.3 Conceptual framework and methodology

Rising global energy consumption and emissions pose a serious threat to the global economy (N. Stern 2008). Although there is limited research into the role of data centres in the energy system, there is a broad literature that explains why economic agents fail to engage with energy efficiency. The theory underlying the “Energy Efficiency Gap” posits that goods with a positive net present value are not as widely adopted as they should be (Gerarden et al. 2015; Jaffe and Stavins 1994a). This gap is explained by market failures, model measurement error and behavioural factors.

In studying improved energy efficiency of consumer durable appliances in the 20th century, Newell et al. (1999) found that autonomous technical change, standards and energy prices all influence the range of products on offer. In many cases, there is ample information on market participants and their purchasing decisions. Researchers are challenged by the lack of information in markets where purchasing decisions are not observable. In such cases, modelling technology diffusion serves a helpful purpose.

This study considers how energy efficient server cooling technology could be adopted in the Irish data centre market to reduce energy use. Given the lack of private information on data centres, modelling market adoption helps quantify the potential benefit of upgrading, which could be used to design effective policies. It is especially helpful when public data are limited, as is the case with data centres, which are often privately. Early applications of diffusion have studied mortality (Gompertz 1825) and economic growth (Prescott 1922). Epidemic models of technology diffusion are based on the concept that potential adopters adopt the technology after observing its effectiveness. Their flexibility has been used to model the spread of computerised firm processes (Karshenas and Stoneman 1993) and the diffusion of mail services worldwide (Pulkki-Brännström and Stoneman 2013).

Jaffe and Stavins (1994a) note that the adoption of economically superior technologies is never instantaneous. In fact, market adoption usually approximates a sigmoid (s-shaped) curve. Technology adoption has been studied across a range of contexts: Energy efficient durable consumer goods (Bass 1967), patterns of wind energy diffusion following policy interventions (S. W. Davies and Diaz-Rainey 2011), the diffusion of electric vehicle charging points in Stuttgart over time (Wirges et al. 2012).

Baptista (1999) summarises key work in the area of induced diffusion. S-shaped diffusion features a slow initial uptake followed by growth as the product becomes more widely adopted before slowing down again as the market saturates. Davies and Diaz-Rainey (2011) apply the Bass model (1967) to sales data of consumer durable goods to model the expected diffusion of new technologies.

Equation 4.1 denotes the general diffusion framework, where the change in diffusion (P) between two periods ($t, t+1$) depends on the speed of diffusion (b), the current penetration rate relative to saturation ($P(t)$) and exogenous 'external' effects, such as advertising, marketing or government interventions (a). Where this is not present, $a = 0$.

$$\frac{\{P(t+1) - P(t)\}}{\{1 - P(t)\}} = a + bP(t) \qquad (4.1)$$

The Gompertz curve is considered a better fit than the logistic curve to reflect technology diffusion (Yamakawa et al. 2013). The Gompertz function (Equation 4.2) is an asymmetric curve, where the growth in a period (w) is a function of the maximum growth rate (w_{max}) which is 1 for full market adoption, a constant (k) and the difference between the mid-point (t_m) and end point (t):

$$w = w_{max}e^{-e^{-k(t-t_m)}} \qquad (4.2)$$

One limitation of the Gompertz curve is that it reaches its asymptotic peak at infinity. Yin et al. (2003) adjust the curve to feature a defined end-point (t_{ie}) and mid-point (t_{im}). Following Equation 4.3, for any given period (i) the proportional level of diffusion (λ_{it}) is related to the end- and mid-points of the specified horizon:

$$\lambda_{it} = \left(1 + \frac{t_{ie} - t_i}{t_{ie} - t_m}\right)\left(\frac{t_i}{t_{ie}}\right)^{\frac{t_{ie}}{(t_{ie} - t_{im})}} \qquad (4.3)$$

This paper considers the rate of diffusion of an energy efficiency technology (liquid server cooling) in the data centre sector in Ireland. The rate of diffusion determines how quickly the new technology is adopted and therefore the amount of energy saved each year.

This paper follows Yin et al. (2003) and assumes full market adoption by the end of 2028, which is consistent with the horizon forecast of data centre capacity developed by EirGrid, the Irish Transmission System Operator (EirGrid 2019).

Following Equation 4.3, the symmetric 's-shaped' adoption curve (Yin et al. 2003) is chosen as it is more representative of market behaviour than a constant adoption rate each year (Figure 4.2). Following this curve, initial adoption is slow, but increases as other firms observe the technology is viable. As the technology approaches full market adoption, growth slows due to saturation. Figure 4.2 illustrates the market adoption pattern, with adoption beginning in 2020 and ending in 2028, a nine-year period where the market reaches fifty percent saturation four and a half years into the horizon (mid 2023).

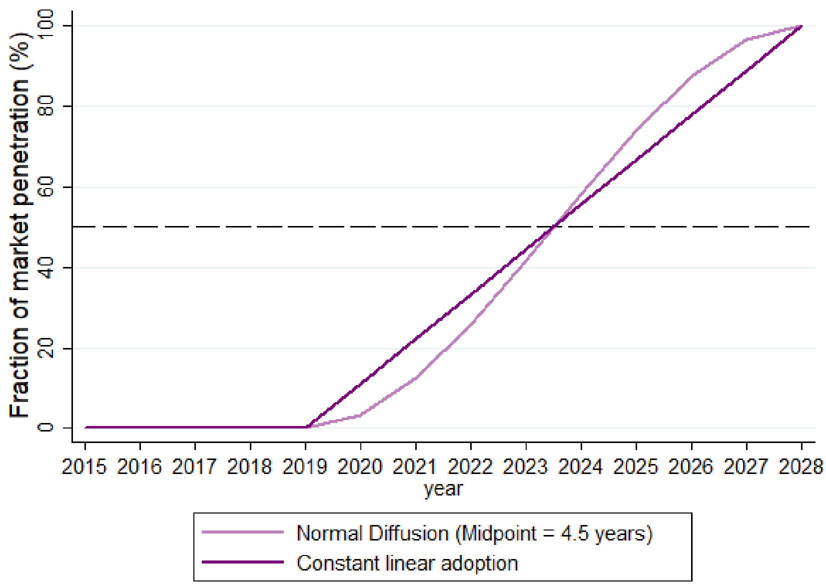


Figure 4.2: Author's comparison of linear and s-shaped market diffusion (2019-2028)

4.3.1 Assumptions

This study applies a model of technology diffusion to quantify the potential for liquid cooling technology to lower data centre energy use in Ireland. Given the lack of publicly available data, assumptions are needed regarding the composition of data centres:

1. The market consists of identical data centres using standard mechanical air cooling.
2. A form of direct liquid cooling for computer server cooling is adopted. This is chosen for two reasons: Firstly, rising demand for data services will require denser computer servers that require advanced liquid cooling. Secondly, increasing energy and climate

awareness will spur interest in technologies that help reduce energy consumption and that have an additional benefit in reusing waste heat.

3. The liquid cooling technology is assumed to provide a 33% reduction in data centre electricity demand (following Garimella et al. (2013)). The additional benefit of reused waste heat is not quantified but is noted as an important factor for the commercial viability of liquid cooling adoption (Garimella et al. 2013).

4.3.2 Data sources and scenarios

This study uses a forecast of national data centre capacity from EirGrid (2019). Values are converted from units of mega-volt ampere (MVA) to capacity units of mega-watts (MW). Annual electricity demand is calculated by converting to mega-watt hours (MWh) and multiplying by the number of days and hours, assuming a data centre capacity factor of 0.75 (IWEA (2015)). Changes in electricity demand depend on the share of the market that adopts the new technology. Two types of data centre are considered: Those operational before 2020 ("Existing (E)") and those in the connection process ("New (N)"), per the EirGrid (2019) medium demand forecast. Data centres choose whether to use traditional mechanical air cooling using a vapour compression cycle ("M") or the new liquid cooling that provides a 33% reduction in plant-level electricity use ("L"). Table 4.1 considers three scenarios:

1. Business as Usual (BAU: N_M, E_M): Liquid cooling is not adopted by any plant. Consumption in this case is assumed to match the projection provided by EirGrid.
2. New Only Diffusion (ND: N_L, E_M): In this scenario, only the new data centres will adopt liquid cooling as the existing stock of data centres do not adopt the technology. The new data centres adopt liquid cooling in the period they commence operation.
3. All Diffusion (AD: N_L, EL): Both existing and new data centres adopt liquid cooling with the timing of adoption subject to the s-shaped diffusion model.

Table 4.1: Taxonomy of EET adoption scenarios

		Existing data centres (E)	
New data centres (N)		**Liquid (L)**	**Mechanical Air Cooled (M)**
	Liquid (L)	N_L, E_L	N_L, E_M
	Mechanical Air Cooled (M)	N_M, E_L	N_M, E_M

Note: Table lists possible adoption scenarios. N_L, E_L features both New and Existing data centres adopt. N_L, E_M only features adoption for new data centres. N_M, E_M features no adoption and reflects the status quo. N_M, E_L (highlighted) suggests only existing data centres adopt. It is not discussed as it is unrealistic.

4.4 Results

This section presents results following the previously discussed approach. Firstly, results are presented for the data centre sector (Section 4.1). This outlines the scope for efficiencies in data centre cooling over the coming years. This is followed by results presented at the national level (4.2). These results provide context on how Ireland is particularly sensitive to the data centre sector and stands to benefit from any efficiencies in their energy demand. The final set of results (4.3) quantify the reduced emissions as a result of reduced electricity demand. This is an important societal benefit of the reduction in data centre energy use.

4.4.1 Data centre electricity demand

Figure 4.3 illustrates the reduction in data centre capacity associated with each scenario. It highlights the significant scope for reducing data centre capacity in the ND (light blue bar) and AD (dark blue bar) case, depending on the extent of adoption.

Figure 4.4 illustrates the forecast of sectoral electricity demand, including a capacity factor of 0.75. The most interesting comparison is between the Business as Usual (BAU_{MED}) scenario, which EirGrid consider most likely with two adoption scenarios: New Only diffusion (ND, long-dash line) and All Diffusion (AD, dot-dash line), the latter of which assumes that existing data centres also upgrade their cooling technology. In 2028, electricity consumption by data centres would be 6% lower in the “New only diffusion” diffusion (ND) scenario and 33.3% lower in the “All diffusion” scenario (AD).

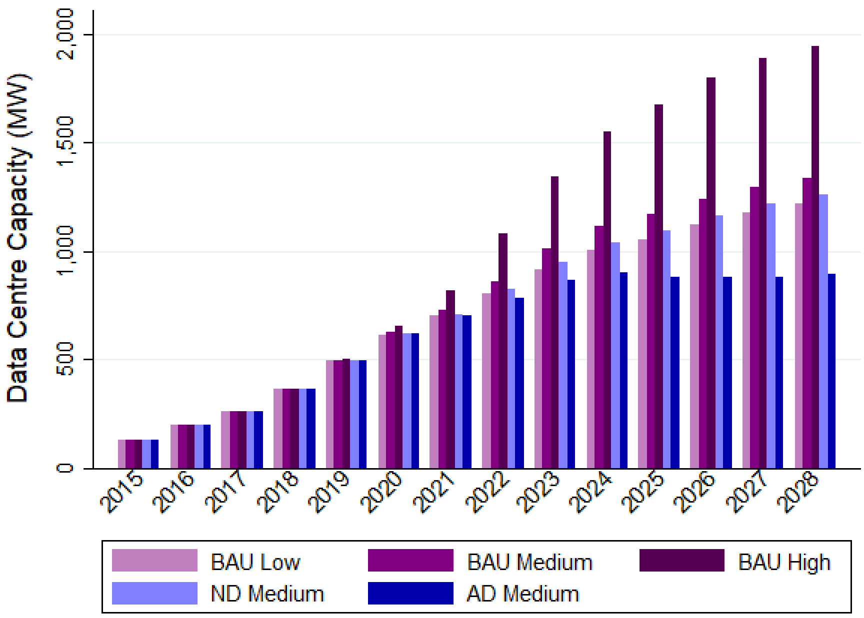


Figure 4.3: Data centre sector capacity (MW)

Source: Author's calculations using EirGrid (2019). Note: Capacities in MW, no capacity factor applied.

This result is consistent with the assumption that technology adoption will reduce data centre energy consumption by a third, but it also emphasises the significant role that existing data centres play in determining the scope for new technology to spur widespread improvement in sectoral energy demand.

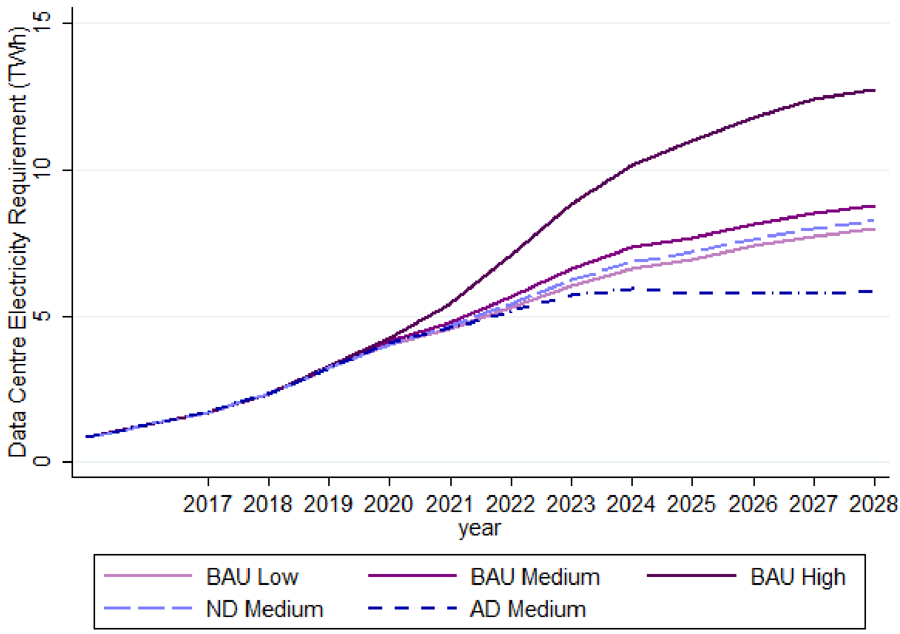


Figure 4.4: Data centre sector electricity consumption (TWh)

Source: Author's calculations using EirGrid (2019). Note: Assumes a data centre capacity factor of 0.75.

Focusing only on the final year of the horizon neglects the cumulative energy savings. Over the nine-year period (2020-2028) when diffusion occurs, the ND scenario lowers energy use by 5.58% over the entire period, while the AD scenario lowers energy use by 21.14% over the same period (relative to the EirGrid BAU_{MED} scenario). This result emphasises the importance of the timing of technology adoption, in addition to which plant choose to adopt.

4.4.2 National electricity demand

This section considers the effect of data centre technology adoption on national electricity demand. When computing a forecast of national energy use, it is important that energy use reflects the difference between the higher BAU level of data centre electricity consumption and the lower sectoral energy use of data centres considered in adoption (ND, AD) scenarios. Equation 4.4 shows how national electricity demand ($NatDem$) for diffusion scenarios is deflated according to the difference in relative share of data centre electricity use as a proportion of the BAU national total electricity demand. $DC\ Cons$ reflects the electricity demand attributable to data centres each year.

$$NatDem_{AD,ND} = NatDem_{BAU\_MED} * \left[1 - \left(\frac{DC\ Cons_{BAU_{MED}}}{NatDem_{BAU_{MED}}} - \frac{DC\ Cons_{AD,ND_{MED}}}{NatDem_{BAU_{MED}}}\right)\right] \quad (4.4)$$

Figure 4.5 illustrates national electricity demand, with the three BAU scenarios where no technology diffusion occurs (EirGrid 2019) compared with the technology diffusion scenarios (long-dash ND line, dot-dashed AD line). In 2028, the ND scenario reduces national electricity consumption by 1.32% relative to BAU_{MED}, while the AD scenario would save 7.31%. Over the nine-year period, the total reduction in electricity demand is 1.03% and 3.94% for ND and AD scenarios, respectively. This result highlights the significant presence of data centres on the national level and emphasises the significant scope for improvements in data centre energy to translate to significant national savings.

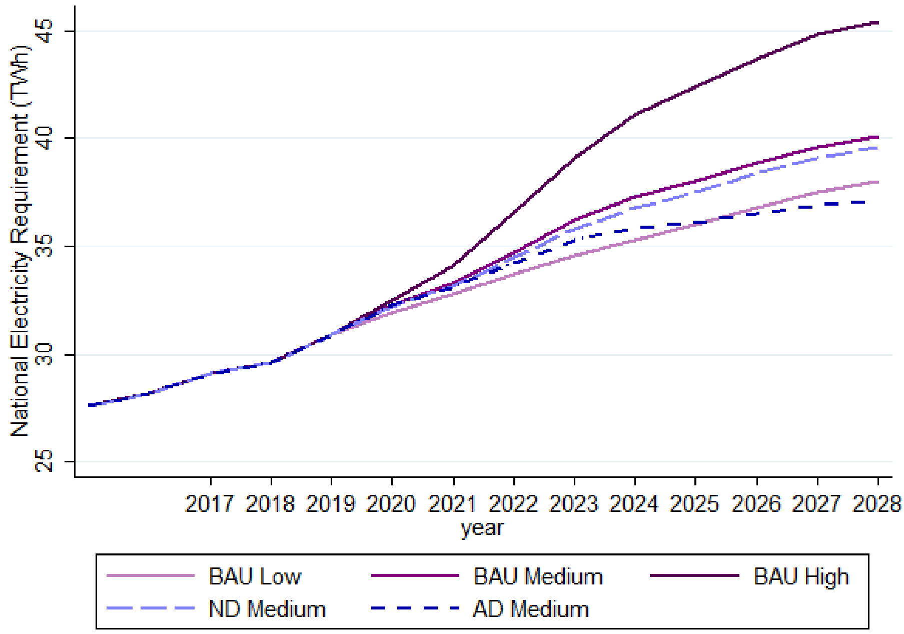


Figure 4.5: National electricity consumption

Source: Author's calculations using EirGrid (2019). Note: Assumes a data centre capacity factor of 0.75.

Table 4.2 highlights the share of national electricity consumption attributable to data centres over time. Every forecast shows data centres comprising a smaller share relative to BAU_{MED}. Based on savings from the 2020-2028 period, the ND scenario reflects a 1.00 percentage point reduction in the national share, from an average of 18.44% under BAU_{MED} to 17.44 under ND. The reduction is even greater for the AD scenario, featuring a 3.76 percentage point reduction in the national share to an average share of 14.69%. This result highlights the large share of data centres in the national context while also highlighting the significant scope for energy savings, especially in the scenario where all data centres adopt the technology in question.

The final two columns of Table 4.2 show how the level of savings is moderated somewhat when the share of data centre consumption is computed as a fraction of the deflated national electricity consumption (following Equation 4.4). For the ND case, the average shares for the 2020-2028 period are 17.63% and 15.28% in the ND and AD scenarios, respectively. This result emphasises the influential role of data centres in the national context, even after accounting for a forecast of national electricity demand that accounts for improvements in data centre efficiency over time.

Table 4.2: Data centre share of national electricity demand

	LOW %	BAU MED %	HIGH %	ND MED** %	AD MED** %
2015	3.12	3.12	3.12	3.12	3.12
2016	4.59	4.59	4.59	4.59	4.59
2017	5.92	5.92	5.92	5.92	5.92
2018	7.99	7.99	7.99	7.99	7.99
2019	10.44	10.44	10.61	10.44	10.44
2020	12.57	12.77	13.12	12.57	12.65
2021	13.98	14.4	15.82	14.04	13.88
2022	15.74	16.3	19.37	15.73	15.11
2023	17.43	18.31	22.55	17.4	16.18
2024	18.68	19.69	24.73	18.6	16.5
2025	19.22	20.21	25.89	19.13	16.02
2026	20.07	20.96	27	19.91	15.82
2027	20.59	21.47	27.7	20.43	15.64
2028	21.03	21.89	28.07	20.86	15.74
2015-2028 Average Share (%)	13.67	14.15	16.89	13.62	12.11
Saving vs. BAU_{MED}				-0.52	-2.03
2020-2028 Average Share (%)	17.70	18.44	22.69	17.63	15.28
Saving vs. BAU_{MED}				-0.81	-3.16

Note: Values are in percent (%). Assumes a data centre capacity factor of 0.75. Note: ND_{MED**}, AD_{MED**} based on deflated value of BAU_{MED} to reflect lower data centre consumption each year. Source: Author's calculations based on EirGrid (2019) data.

4.4.3 Carbon dioxide emissions

Associated with the reduction in energy demand from the data centres are a reduction in CO_2 emissions from electricity generation. The International Energy Agency (IEA) publishes country-specific emissions factors, which relate the level of carbon dioxide (CO_2) emissions to the quantity of energy consumed in a country. However, Brander et al. (2011) note that the IEA reports a composite electricity and heat emissions factor, which might not reflect the actual value of electricity emissions. For data centres whose main energy source is electricity, the correct emissions factor should be adjusted to only reflect electricity consumption.

Table 4.3 presents emissions factors for Ireland based on 2010 energy quantities, accounting for transmission and distribution losses, finding a 7% difference between the IEA composite emissions factor and an electricity specific factor (Brander et al. 2011).

Table 4.3: Electricity specific emissions factors

	$kgCO_2/kWh$	
Electricity-specific generated emissions factor	0.5212	(1)
IEA composite electricity/heat factor	0.4862	(2)
Difference	0.0350 (7.2%)	(1-2)
Electricity transmission & distribution loss emissions factor	0.0449	(3)
Electricity consumed emissions factor	**0.5661**	**(4=1+3)**

Source: Brander et al. (2011) data for Ireland.

The electricity-specific emissions factor of 0.5661 $kgCO_2/kWh$ (Brander et al. 2011) is applied to the electricity consumption in each scenario to quantify the abated emissions associated with improvements in data centre energy efficiency (Table 4.4). Over the 2020-2028 period, emissions would be 4.7% lower for the ND scenario and 23.04% lower for the AD scenario. This result highlights a societal benefit of improving energy efficiency.

This is especially important in the case of Ireland, where fines for non-compliance will result from failing to achieve EU energy efficiency targets. These results are illustrative given that results are sensitive to the emissions factor, which is likely to improve over time as the generation mix for Ireland becomes less carbon intensive. In this sense, these results serve as an upper bound of the potential savings.

Table 4.4: Estimates of data centre CO_2 emissions

		BAU		ND	AD
Year	LOW	MED	HIGH	MED**	MED**
2015	0.49	0.49	0.49	0.49	0.49
2016	0.73	0.73	0.73	0.73	0.73
2017	0.97	0.97	0.97	0.97	0.97
2018	1.34	1.34	1.34	1.34	1.34
2019	1.83	1.83	1.86	1.83	1.83
2020	2.27	2.34	2.41	2.3	2.31
2021	2.6	2.71	3.05	2.64	2.61
2022	3	3.2	4.01	3.09	2.95
2023	3.41	3.75	4.99	3.56	3.26
2024	3.73	4.16	5.75	3.91	3.35
2025	3.92	4.35	6.21	4.1	3.21
2026	4.18	4.61	6.68	4.37	3.12
2027	4.37	4.81	7.02	4.57	3.02
2028	4.52	4.97	7.21	4.72	3.03
2015-2028 Total	37.36	40.26	52.72	38.62	32.22
Saving vs. BAU_{MED} (%)				4.07%	19.97%
2020-2028 Total	32	34.9	47.33	33.26	26.86
Saving vs. BAU_{MED} (%)				4.70%	23.04%

***Note: Values are in units of million tonnes of CO_2 equivalent (Mt CO_2eq), based on national electricity demand and Brander et al. (2011) emissions factors for Ireland. Assumes a data centre capacity factor of 0.75. Note: ND_{MED**}, AD_{MED**} based on deflated BAU_{MED} to reflect lower data centre consumption.**

4.5 Concluding remarks

This chapter is motivated by the recent emergence of data centres that help power the modern economy. In particular, it is interested in the significant pressure they exert on national energy demand. The presence of data centres is a particular challenge for certain economies, such as Ireland, that are already struggling to comply with long term EU targets for improving energy efficiency. Data centres are an example of a rapidly evolving technology that poses a planning challenge for policymakers, with consequences for future energy demand, transmission systems and emissions. Such analysis is made especially complex by the lack of publicly available information on data centres, where the only data source is a forecast of expected data centre capacity. This can hinder decision making under uncertainty.

In order to evaluate whether particular policies in this space would be effective, it is important to first quantify the scope for achievable efficiencies. This paper applies an epidemic model of technology diffusion which can be applied to quantify the potential savings from a specific energy efficiency technology. It serves as a helpful tool when publicly available data are limited. Although the specific technology may change, research has identified cooling as one of the most energy-intensive aspects of data centres. In fact, mechanical cooling can comprise one third of energy use in a data centre (Garimella et al. 2013). This study focuses on eliminating this share of energy use in the data centre, and the consequences this would have on the Irish energy system.

When evaluating technologies that improve data centre energy efficiency, it is important to consider the direct energy savings. It is also important to quantify the external benefit of reduced carbon emissions. Although some benefits do not accrue directly to firms, they are an important consideration for policymakers when formulating possible incentives.

The key finding in this paper is that data centres can serve a key role in fostering improvements in energy efficiency. This is especially true in Ireland, where data centres could use almost 40% of national electricity demand by 2028. Compared to other countries, data centres have a sizeable impact on Irish efforts to energy efficiency and lower energy use. There is potential to reduce national energy use by 3.16% over the 2020-2028 period if every data centre adopts the energy efficiency technology.

The second result is that the level of savings depends on how extensively such technology can be adopted by new and existing data centres. The 3.16% reduction in national electricity demand is only achieved if every data centre adopts. These savings fall to a 0.81% reduction if adoption is not possible for existing capacity. The final result notes the potential to reduce sectoral emissions by 23.04% over the period 2020-2028, depending on the level of technology adoption. This is a significant saving that serves as added motivation for policymakers to foster improvement in data centre energy efficiency.

Certain topics are beyond the scope of this study. Although future market trends cannot be predicted, technological innovations are expected. It is for this reason that the paper has taken a technology-agnostic approach. Advancements in energy generation, transmission and interconnection will also matter, as the current results for emissions reduction are a function of the carbon-intensity of electricity generation in Ireland. However, changes in legislation and political events may serve as demand shifters for the data centre sector.

It is important to emphasise that a major contribution of this paper lies in its methodology and how this is applicable to a variety of contexts where forecasts must be made under uncertainty. It features flexibility to respond to new forecast horizons and alternative technologies within the data centre and the wider transmission network. It evaluates the scope for data centres to deliver energy savings through technology adoption. It does not consider the cost of the technology, in new-build data centres or retrofitted to existing plant. A more substantial cost-benefit analysis would be required to determine if the net present value of energy savings outweighs the marginal capital costs of adoption.

Results highlight the potential savings and suggest that policymakers should aim to foster improvements in energy efficiency. This may be attainable given the relatively small number of firms in the market and their existing working relationship with EirGrid, the transmission system operator, formed during the planning and connection process. Another recommendation is that policymakers publish a more detailed record of data centres in Ireland and the efforts firms have made to improve energy efficiency. This has been effective at EU level, with the Data Centre Code of Conduct for Data Centre Energy Efficiency (European Commission 2016) that has been associated with improvements in average Power Usage Effectiveness (Avgerinou et al. 2017).

4.A Technical literature on data centre server cooling

This section presents a non-technical overview on various server cooling techniques within data centres. Although this is not the primary focus of this study, it may offer helpful context to readers. A substantial literature exists on server cooling technology (see Ebrahimi et al., 2014). In most data centres, servers are fan-cooled with a power-hungry mechanical chiller. A mechanical chiller can be responsible for one third of facility energy consumption (Garimella et al. 2013). One innovation has been air-side economization ('free air' cooling) which reduces energy costs by using filtered outside air to cool servers instead of a mechanical chiller. 'Free air' cooling is popular in temperate climates, especially for 'hyper scale' facilities. Song et al. (2015) found that 'free air' cooling could reduce consumption by up to 35% compared, depending on location, weather and energy prices.

Another technology is direct liquid cooling, which pipes liquid through the computer server to remove heat. The use of direct liquid cooling has typically been required for High-Performance Computing (HPC) units. However, it is suspected that typical data centres may require liquid cooling to operate effectively in the future[31]. To remove heat, Greenberg et al. (2006) note that liquid has a much higher thermal carrying capacity than air, being able to carry 3,500 times more heat. In studying a HPC unit in the USA, Sickinger et al. (2014) find that a direct liquid cooling unit (Asetek RackCDU) was easy to retrofit to the existing supercomputer. Contrary to industry concerns about liquid cooling leakage, there was no maintenance or leaks during 16 months of operation and over half of the heat emitted from the central processing unit (CPU) could be recovered. This shows how direct liquid cooling could eliminate the need for a mechanical chiller while reducing and reusing energy. The liquid cooling system also halved the floor space required, an additional benefit.

The management of waste heat is of interest to data centres given their significant level of electricity consumption. With waste heat capture data centres could potentially meet data centre heating needs, replace power used in computer server cooling process, heat nearby premises or even convert waste heat to electricity and supply to the national grid (Ebrahimi et al. 2014).

[31] See http://www.datacenterknowledge.com/archives/2014/08/14/is-direct-liquid-cooling-making-a-comeback/

The higher temperature of heat recovered via liquid cooling makes it the preferred means, although there is a trade-off between the quality of the waste heat collected and effectively cooling servers (Carbó et al. 2016). An Apple data centre located in Jutland, Denmark, plans to use data centre waste heat in nearby homes[32] as part of an existing district heating network which supplies 64% of homes[33]. Other work has noted the potential for data centres within a district heating network, but the significant capital cost of district heating remains a hurdle in many cases (G. F. Davies et al. 2016; IRBEA 2016). If reusing waste heat is socially optimal, but data centre operators do not benefit from spending the extra capital to capture waste heat then it is important to consider policies that could help incentivise this behaviour to reach the socially optimal outcome. Table 4.5 provides a non-technical overview of popular cooling methods, including key drawbacks and benefits.

Table 4.5: [4A] Summary of data centre server cooling technologies

Cooling Type	Benefits	Limitations
Conventional Air Cooling (Mechanically chilled air is channelled through server rack.)	Cost effective Scalable Location-friendly Widely used	Mechanical chilling process is energy intensive Fan cooling inefficient, loud, short fan lifespan Difficult to reuse waste heat
Free Air Cooling (Outside air is channelled through server rack.)	Cost effective No mechanical chilling required Used for “hyper-scale” facilities	Not suitable at all scales Somewhat location specific Extra work to manage humidity, particles Adverse working conditions (noise, heat)
Direct Liquid Cooling (Closed loop of liquid is channelled through server rack to dissipate the heat.)	Optimal server cooling Excellent waste heat extraction – suitable for district heating Likely needed for more computing power	More costly Not proven at “hyper scale” Not widely used Reluctance to adopt liquid

32 See http://www.usadk.org/news/apple-establishes-one-of-the-worlds-largest-data-centres-in-denmark/
33 See http://www.investindk.com/Clusters/Cleantech/Data-Centres

Figure 4.6 illustrates a conventional data centre, with servers arranged in 'hot' and 'cold' aisles to disperse heat. Mechanically chilled air is channelled through the floor into the servers. In contrast, a liquid-cooled facility would replace the mechanical air conditioner unit (CRAC) with a closed loop of fluid channelled through the server to remove heat effectively. There is general agreement on the continued increase in effective power density (Garimella et al. 2016). However, advances in cooling technologies could offset rising energy demand.

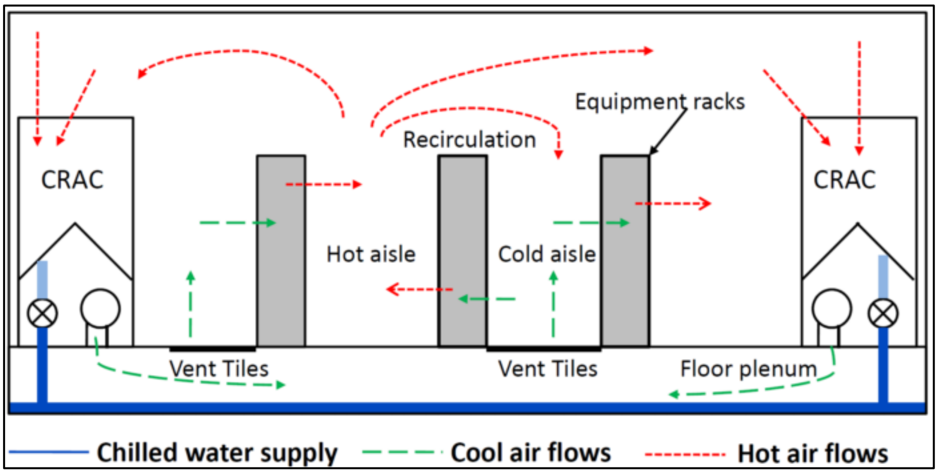


Figure 4.6: [4A] Traditional data centre layout

Source: (Zhou et al. (2011))

In summary, data centres aim to minimize their capital and operating costs. For most, this means using mechanically chilled air cooling, especially in regions with low electricity prices. For other facilities, the use of free air cooling avoids the need for a power-hungry mechanical chiller. Direct liquid cooling has the potential to reduce data centre energy consumption and maximise the potential for recapturing waste heat.

Chapter 5: The multiple benefits of large-scale energy efficiency technology adoption

5.1 Introduction

The EU set binding targets for renewable generation, emissions reduction and energy efficiency to achieve climate neutrality by 2050 (European Commission 2019a). 2030 climate targets include i) reducing GHG emissions by 40% from 1990 levels, ii) 32% of the energy mix from renewable sources and iii) 32.5% improvement in energy efficiency, relative to a 2007 forecast (European Parliament 2018). Heating and cooling comprise 48% of global energy use and 39% of CO_2 emissions (REN21 2019).

Data centres consume one per cent of global electricity demand (Masanet et al. 2020). Conventional data centre cooling involves grid-powered chillers sending cold air to servers, comprising a third of facility electricity use (Garimella et al. 2013). In some cases, data centre waste heat contributes to a district heating network providing heating to two thirds of Danish households (Danish Energy Agency 2015). Data centres could meet heating demand in urban areas such as London (G. F. Davies et al. 2016) and Dublin (Gartland 2015; IRBEA 2016). Studies to date are limited to the plant (Wahlroos et al. 2018) and city level (G. F. Davies et al. 2016), while advanced liquid cooling features in experimental server-level studies (Sickinger et al. 2014).

An integrated energy system of electric and thermal fuels could accommodate rising energy demand while increasing generation from renewable sources (O'Malley et al. 2016). However, energy efficiency has yet to fulfil its potential due to the continued use of inefficient technologies, a lack of effective policy and weak investment (IEA 2020). For example, Persson et al. (2014) estimates that 46% of European waste heat could be reused, with correct incentives. Differences between the private and social optimal outcome contribute to underinvestment in energy efficiency (Jaffe and Stavins 1994b).

One under-researched area is the potential for energy efficient technology (EET) that simultaneously eliminates data centre cooling demand while supplying low-carbon energy for use elsewhere. This is relevant due to the ascension of data centres and the pressing need to reduce energy use and emissions globally. The lack of evidence to date possibly stems from the different investment perspectives (Arrow and Lind 1978), market failures (Gerarden et al. 2017) or the lack of commercially available technologies.

This is the first paper to evaluate the national economic benefit of an EET that fosters energy systems integration. It connects two distinct strands of literature on small-scale data centre energy efficiency and large-scale consequences of data centres on power systems. This paper considers a commercially available large-scale technology that uses a charging cycle to convert electricity into hot and cold thermal energy. It stores electricity, facilitates increased RES generation and helps improve system demand response. This is studied for Ireland, a country with an ambitious target of generating 70% of energy from renewable sources by 2030 (Government of Ireland 2019), where reducing emissions in heating has proven challenging (SEAI 2019) and where data centres are forecast to drive 75% of the growth in national electricity demand from 2017-2026 (Oireachtas 2017).

Results model a representative data centre paired with the EET at the national level using a forecast of Irish data centre construction. Indirect benefits estimate the hot water available for use in another sector due to technology adoption. Tertiary benefits are quantified using ENGINE, a power systems model of the Irish economy (D. Z. Fitiwi et al. 2020). Although results are specific to Ireland and the EET considered, it represents an important example of the potential for sector coupling to help achieve climate targets. It also provides a methodology that can be applied to other technologies, industries and power systems.

The paper is presented as follows: Section 5.2 provides global policy context. Section 5.3 provides context to the Irish case study. Section 5.4 details the research questions of this paper and provides a theoretical basis within the context of the Energy Efficiency Gap. Section 5.5 details the empirical approach of this paper, including scenario details and model inputs. Section 5.6 presents and discusses the results. Section 5.7 concludes.

5.2 Policy context

5.2.1 Global energy demand and data centres

Energy demand is rising globally, with significant increases in electricity use across developed economies. The International Energy Agency (IEA) assert that energy efficiency could be responsible for 80% of the reduction in future global energy use (IEA 2016). However, improvements in energy efficiency are under-exploited due to the use of less efficient technologies, a lack of effective policy and weak investment (IEA 2020). Data centres are estimated to consume one per cent of global electricity (Masanet et al. 2020). Their presence has risen as internet connectivity has become a "key economic asset" (European Commission 2017b). Data centres are critical for information storage, communication and computing and can unlock future innovations including driverless cars (Macauley 2016), 5G connectivity and machine to machine activity (OECD 2017).

Improvements in data centre energy efficiency over time largely stem from improvements in computing electrical efficiency, which has doubled every 1.5 years in accordance with Moore’s Law since its inception in the 1960s (J. G. Koomey et al. 2011). Shehabi et al. (2018) forecast 2020 US data centre electricity use around 70 billion kWh, noting how rising energy efficiency has prevented electricity use from rising proportionally with increases in data workloads. However, this relationship is contingent on the nature and diffusion of future energy efficiency technologies (Shehabi et al. 2018).

Koronen et al. (2020) notes that EU data centre energy efficiency policies are limited to voluntary schemes and research funding. The voluntary Code of Conduct for Data Centre Energy Efficiency (European Commission 2016) highlights best practice in optimising data centre energy efficiency. For 289 participants, the average Power Usage Effectiveness (PUE)[34] has fallen from 1.9 in 2010 to 1.64 in 2016, suggesting a positive effect of the policy (Avgerinou et al. 2017). Other global survey data suggests the average PUE has fallen from 2.5 in 2007 to 1.58 in 2018 (Uptime Institute 2018). However, PUE is an unreliable metric, especially when quantifying efficiencies involving waste heat reuse outside the facility (Brady et al. 2013; Horner and Azevedo 2016; Yuventi and Mehdizadeh 2013).

[34] PUE is defined as the total facility energy use divided by IT energy use.

5.2.2 Data centre energy efficiency potential

The private ownership of many data centres makes monitoring energy use difficult (Whitehead et al. 2014). In a conventional data centre, computer servers require cooling to maintain operational temperatures. Cold air is generated by a mechanical chiller, passes through the servers, and exits the server as warm air. This process can represent a third of data centre electricity use (Garimella et al. 2013). However, larger ‘hyperscale’ data centres achieve greater efficiency using ambient air cooling to reduce total energy use.

Aside from more efficient IT hardware, data centres could increase energy efficiency by recycling exhaust air (Ebrahimi et al. (2014) to supply a district heating (DH) network (G. F. Davies et al. 2016; Wahlroos et al. 2018). In most cases, low grade waste heat is boosted by heat pump to a suitable temperature. However, this is less of an issue for the latest 4th Generation DH systems that operate with a supply temperature of $45 - 55$℃, rather than the current 3rd Generation DH networks that require $75 - 120$℃ (Wahlroos et al. 2018).

Research has highlighted the potential for data centres to meet heating demand in densely populated regions with no existing DH network such as London (G. F. Davies et al. 2016) and Dublin (Gartland 2015; IRBEA 2016). One underdeveloped area is the possibility of adopting an energy efficient technology that simultaneously eliminates data centre energy demand for cooling while also supplying energy for use in other sectors.

5.3 Research setting - Ireland

Ireland has a poor record in decarbonising heating (SEAI 2019), a large share of intermittent renewable energy sources (RES) and untapped potential for district heating (IRBEA 2016). By the end of 2018, Ireland has only realised 69% of their 2020 EU target for energy generation from renewable sources, 72% of the renewable transport target, 83% of the renewable electricity target and only 54% of heat from renewable sources (SEAI 2019). Improving energy efficiency forms a key part of national climate policies (DCCAE 2017b). Ireland has become the centre of the digital economy, conducting 14% of global trade in ICT services in 2016 (OECD 2017), the highest of any country.

Data centres locate in Ireland for the electricity supply (Schwab 2015), affordable business units (IWEA 2015), fibre internet (Bitpower and Host in Ireland 2017) and ease of doing business (William Fry 2016)[35]. However, firm-level decisions to locate data centres in Ireland have national consequences. Data centres are expected to comprise 75% of the growth in Irish electricity use from 2017-2026 (Oireachtas 2017). By 2028, it is projected that data centres will use between 25% and 37% of national electricity (EirGrid 2019).

Less than one per cent of Ireland's heat demand is met through district heating (DH), below the EU average (7%) and Denmark, where over 60% of residential area is heated by DH (IRBEA 2016). The national Climate Action Plan aspires to have 60,000 DH-connected homes by 2040 (Government of Ireland 2019). Two DH projects have received grant support from the Climate Action Fund, one of which will reuse data centre waste heat with a heat pump to supply space and water heating for 1,962 homes, 16,250m^2 of commercial space and 47,000m^2 of public buildings (CODEMA 2018a). Ireland is the perfect case study for the effectiveness of an energy efficiency technology (EET) that lowers data centre energy use, decarbonises the heating sector and increases grid-level electricity storage.

5.4 Economic theory and research questions

5.4.1 Economic theory

This paper considers one example of how differences in public and private investment decision making can result in a lack mutually beneficial projects. One explanation for the lack of collaboration is the different discount rate, with private sector investments often requiring a higher discount rate to invest (see Solow (1963), Arrow & Lind (1978)). This paper contributes evidence to the Energy Efficiency Gap, which theorizes there is a relative social under-adoption of energy efficient technologies with a positive net present value (Jaffe and Stavins 1994a).

[35] Appendix 5.A details a survey by IDA Ireland on the economic benefit of data centres to the Irish economy.

Jaffe & Stavins (1994b) argue that market failures such as information problems, principal-agent issues and unobserved costs warrant government intervention, whereas non-market failure factors, including high customer discount rates, private information costs and adopter heterogeneity should not warrant government intervention. Gerarden et al. (2017) considers the three broad areas of market failures, behavioural factors and model measurement error to be the main drivers of the Energy Efficiency Gap.

Allcott & Greenstone (2012) consider a model of investment in energy-using durable goods to distinguish between (1) investment inefficiencies which may prevent consumers making 'optimal' purchases and (2) energy use externalities, which result in energy use being priced at a socially optimal rate. The Energy Efficiency Gap acts as a weight on perceived energy cost savings, capturing investment inefficiencies when a consumer compares extra investment today with future energy savings. Examples include consumer inattention, the cost of information and differences in the interest rate and the risk-adjusted discount rate. This paper asserts that the EET would not be adopted by either policymakers or data centre operators alone, since the benefits accrue to both private (cheaper data centre cooling) and public (heating energy source, transmission network savings) agents.

5.4.2 Research questions

This study considers the economic benefit of an integrated energy system in terms of energy savings, where an energy efficiency technology (EET) facilitates increased penetration of renewable generation, which offers a low/zero carbon supply of cooling to data centres and heating to an alternative source. This is investigated across three specific research questions:

RQ1: What is the **primary** benefit of data centre cooling energy savings?
RQ2: What is the **secondary benefit** of heating energy savings?
RQ3: What are the **tertiary benefits** of EET adoption?

RQ1 considers the primary benefit of reduced energy use resulting from data centres availing of free cold-water supply from the EET (detailed in Section 5.2). RQ2 quantifies the secondary benefit of EET adoption in terms of hot water supply that could displace fossil-based heating.

RQ3 quantifies the tertiary benefit to the wider transmission system associated with EET adoption in terms of grid-level investment and emissions, using a model of the Irish energy system in 2030.

This study makes several important contributions. The first outlines the economic benefit of the chosen EET in terms of energy usage. The second contribution is the use of a unique dataset on forecasted plant-level data centre capacity. The third contribution is the results for the Irish energy system offered by the power system optimisation tool ENGINE, which acts as an approximation of the 'public good' benefit of technology adoption in terms of renewable generation capacity, system-wide curtailment and emissions.

5.5 Methodology and data

5.5.1 Methodology

Figure 5.1 details the analysis. The first step involves designing a plant-level model of a data centre paired with the EET. Following this, the representative facility is considered within a market-level forecast of data centre capacity for the period 2019-2028. Finally, the power systems model quantifies the tertiary benefit of technology adoption in 2030.

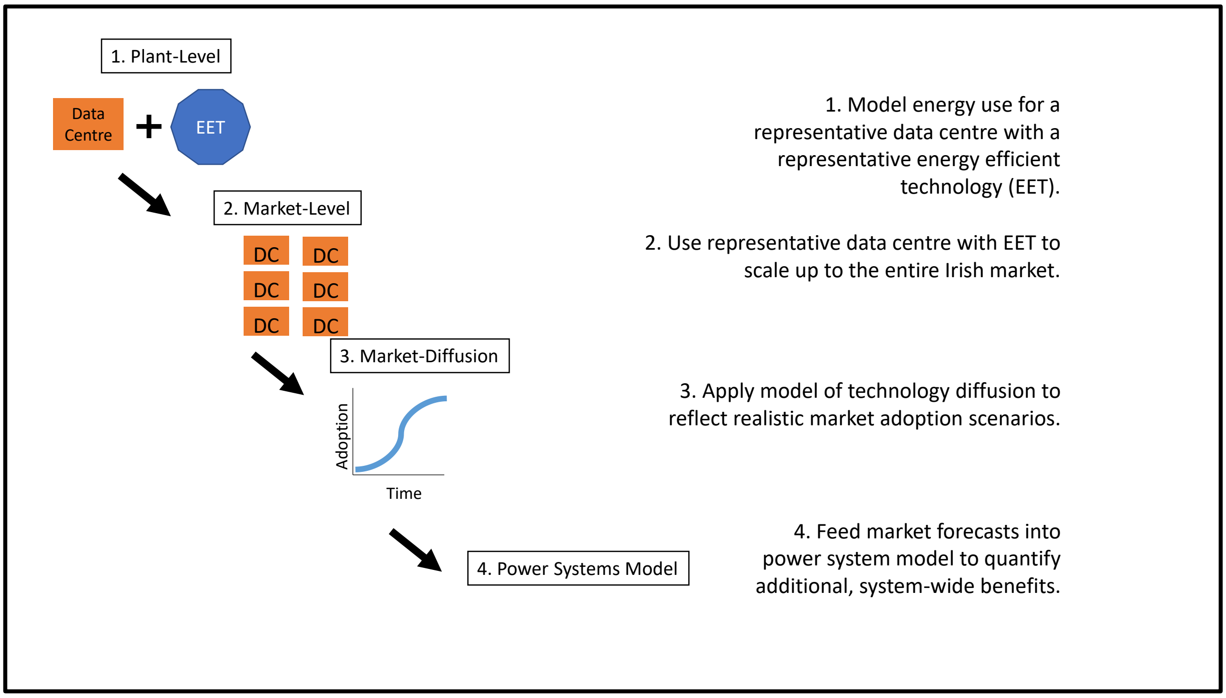


Figure 5.1: Data collection and methodology

This study models energy balances for a representative data centre that adopts the EET and builds an annual forecast based on national data centre planning applications. Four scenarios are considered: A Business as Usual (BAU) scenario with no EET adoption ($H0$) is compared with three EET adoption scenarios with differing heating use: A low-temperature future 4th Generation District Heating system ($H1$), a high temperature 3rd Generation District Heating system ($H2$) and an industrial use of hot water ($H3$). In each EET scenario ($H1 - H3$), data centre cooling is displaced by cold water supply from the EET.

Results are sensitive to the assumed utilization rate (U) of the data centre i.e. what fraction is a data centre operating at its planned maximum capacity. This study infers energy demand (and cooling requirements) from planning capacity information for data centres. Results assume that data centres operate at their maximum utilization (UM) - reflecting the theoretical maximum energy use. Table 5.5.1 outlines the taxonomy of scenarios considered.

Table 5.1: Taxonomy of scenarios

Heating End Use (H)	**Data Centre Utilization (U)**
	UM = 100%
H0: Business as Usual	H0, UM
H1: 4GDH (Future)	H1, UM
H2: 3GDH (Current)	H2, UM
H3: Industrial	H3, UM

Note: 4GDH refers to an emerging 4th generation low-temperature district heating network. 3GDH refers to an existing high-temperature 3rd generation district heating network. Industrial refers to a setting where an industry with a specific demand for hot water locates adjacent to the data centre.

Plant-level results in Section 5.6.1 calculate annual energy use for data centres. For data centre i with heating end use H, data centre utilization rate U and year t, Equations 5.1, 5.2 and 5.3 describe how capacities are converted to annual values in units of megawatt-hours (MWh) for Total energy use ($eTotal$), IT electricity use (eIT) and Cooling energy use ($eCooling$). Three types of data centre are considered, based on EET adoption status (a): facilities that are incompatible with the EET, facilities that are EET compatible but are already built ($a = 1$) and facilities that are EET compatible but are planned. Only the latter group adopts the EET.

$$eTotal_{i,H,U,t} = Capacity_{i,H,U} * 24 * 365 \quad [5.1]$$

$$eIT_{i,h,u,t} = ((Capacity_{i,h,u} * 24 * 365)/1.3) * 1 \quad [5.2]$$

$$eCooling_{i,h,u,t} = ((Capacity_{i,h,u} * 24 * 365)/1.3) * 0.3 \quad [5.3]$$

Market-level analysis in Section 5.6.2 aggregates electricity consumed by data centres across each of the four scenarios. Equation 4 defines total market energy use ($meTotal$) in a given year t as the weighted sum of energy use for data centres that are too small to adopt ($a = 0$), data centres that are large enough to adopt but are already built ($a = 1$) and data centres that will adopt ($a = 2$), depending on the heating end use. Equations 5.5 and 5.6 denote the annual electricity use for IT and cooling, respectively.

$$meTotal_{H,U,t} = \sum_{i=1}^{n} eTotal_{i,H,U,t} * w_{a,t} \quad [5.4]$$

$$meIT_{H,U,t} = \sum_{i=1}^{n} eIT_{i,H,U,t} * w_{a,t} \quad [5.5]$$

$$meCooling_{H,U,t} = \sum_{i=1}^{n} eCooling_{i,H,U,t} * w_{a,t} \quad [5.6]$$

5.5.2 Energy Efficiency Technology

The majority of commercial solutions that cool data centres while producing high-grade heat output are based around hot air recovery and a heat pump. Examples of this include an upcoming district heating scheme (DH) in Ireland (CODEMA 2018a), data centres in the Nordic countries supplying an existing DH network, including an Apple data centre in Denmark (Wahlroos et al. 2018). In order to conduct the analysis, the researcher had to choose a technology. However, the same method could be applied to other technologies.

This study considers a large scale, commercially ready technology that provides high-grade heat output and cold supply for a data centre. The MAN Electro Thermal Energy Storage (ETES) system is the chosen EET. Fundamentally, ETES[36] serves as a source of large-scale electricity storage, using a charging cycle to convert electric into thermal energy. ETES aims to further energy systems integration in three ways. Firstly, it provides data centre cold air supply using chilled water. Secondly, ETES hot water supply could displace fossil fuel used for heating. elsewhere Finally, the storage ability of ETES can benefit the national transmission system by lowering grid investment costs, reducing the need for additional renewable electricity capacity expansion and lowering generation-related emissions.

ETES can operate at a range of temperature settings, which influences the capital cost and required electrical input. Key literature informs the supply and return temperature parameters across three possible heating end-uses ($H1, H2, H3$). Table 5.2 summarizes the assumed supply and return temperatures for cold and hot water in analysis**.**

Table 5.2: Temperature assumptions for ETES system

Temperature (degrees Celsius)	**Heating End Uses**		
	H2: 3GDH	**H1: 4GDH**	**H3: Industrial**
Cold water supply	18		
Cold water return	27		
Hot water supply	90	60	120
Hot water return	50	20	50

Source: Consultation with MAN. Note: 4GDH refers to an emerging 4th generation low-temperature district heating network. 3GDH refers to an existing high-temperature 3rd generation district heating network. Industrial refers to a setting where an industry with a specific demand for hot water locates adjacent to the data centre.

Cold-water: The EU Code of Conduct on Data Centre Energy Efficiency suggests that data centres should deliver air to the IT equipment within the $10-35°C$ range (European Commission 2014). This is consistent with ASHRAE industry standards, which recommends inlet temperatures between $18-27°C$ (Uptime Institute 2015). In this study, a cold supply temperature of $18°C$ and a cold return temperature of $27°C$ is assumed.

[36] Appendix 5.B includes additional information on the specifics of the ETES charging cycle.

Hot-water supply: Hot water temperatures depend on the heating end-use. $H1$ considers a 4th generation District Heating system that integrates heat, electricity and energy storage with energy efficient buildings (Lund et al. 2014). It is assumed to require a supply temperature of $60°C$ with a return of $20°C$. $H2$ considers existing 3rd generation DH systems that assumes a supply temperature of $90°C$ and a return temperature of $50°C$ (Lund et al. 2014). $H3$ considers an industrial heating end-use where hot water is supplied at $120°C$ and returned at $50°C$. It is assumed that the industrial user is located adjacent to the EET, similar to the upcoming Tallaght District Heating Scheme in Ireland (CODEMA 2018a).

Table 5.3 summarizes EET efficiency for the three heating end uses based on an eight-hour charge. The higher coefficient of performance (COP) for $H1$ reflects the most efficient case. Conversely, there is a higher Hot Duty for $H2$ and $H3$, reflecting the higher supply temperature and the additional power input required. Appendix A.2 illustrates the negative relationship between charging time and both the power input and storage size of the EET.

Table 5.3: ETES system efficiency parameters

Heating End Use ($\boldsymbol{H}$)	Utilization ($\boldsymbol{U}$)	Hot COP	Cold COP	Assumed Cold Duty (MW)	Hot Duty (MW)	8H Power Input (MW)
$\boldsymbol{H1}$: 4GDH	1.0	4.63	3.59	6.84	8.84	5.72
$\boldsymbol{H2}$: 3GDH	1.0	2.68	1.60	6.84	11.48	12.86
$\boldsymbol{H3}$: Industrial	1.0	2.68	1.60	6.84	11.47	12.84

Note: Based on a 29.64 MW data centre, which provides assumed values for Cold Duty. Hot and Cold COP, Hot Duty obtained from MAN. Power Input based on 8-hour charging time.

5.5.3 Data centre market data

This paper uses a unique data set of data centre planning applications compiled by Bitpower (2020)[37]. The data features 112 plant-level observations with details on location, type, development status, year of construction, design capacity (in MW) and IT Power (assuming an average PUE of 1.3).

[37] This study used 112 of 116 facilities in the Bitpower data to approximate the Irish Transmission System Operator forecast for 2030 data centre capacity (EirGrid 2017). Development status is used as an indicator for year operational. 'Under construction' facilities in 2019 (n=5) and 2020 (n=6) are assumed to operate in 2020. Projects with planning approval (n=25) are assumed to be built the year following construction. Projects with planning applications (n=9) or masterplan (n=6) are assumed to be operational two years from construction.

Table 5.4 summarizes the difference in average capacity for data centres that are EET compatible, split by development status. Technical guidance determined that data centres under 20MW are not economically viable for use with the EET due to economies of scale. Of the 47 data centres are at least 20MW (EET compatible), the average capacity is 29.80 MW. Of these, 15 are already built, while 32 are planned. Of the 65 facilities that are too small to be compatible, their average capacity is 8.52 MW.

Table 5.4: Irish data centre market (1997-2028)

Data centres design capacity (MW)	**N**	**Mean**	**Median**	**SD**	**Min**	**Max**
All Data Centres (1997-2028)	112	17.45	15	12.57	0.5	50
Data Centres (Not EET Compatible)	65	8.52	9	5.37	0.5	19.20
Built (1997-2019)	46	7.43	7.68	5.64	0.5	19.20
Planned (2020-2028)	19	11.15	10	3.61	5.46	16
Data Centres (EET Compatible)	47	29.80	30.45	8.53	20	50
Built (1997-2019)	15	28.56	29.28	6.73	20	38.44
Planned (2020-2028)	32	30.39	33.22	9.29	20	50

Source: Data centre capacity information from Bitpower. Data centres assumed PUE of 1.3, meaning that 30% of energy use is for cooling. EET compatible threshold of 20MW capacity determined in consultation with MAN.

Figure 5.2 illustrates the future Irish market, split by development status and EET compatibility. The 112 plant-level observations reflect, in order: 46 data centres that already built and too small to adopt the EET, 19 facilities that are planned but too small to adopt, 15 facilities which are of sufficient scale to adopt but are already built and 32 facilities which are sufficiently large and are planned, respectively. Appendix A.3 provides a breakdown of expected data centre capacity and EET compatibility on a regional basis.

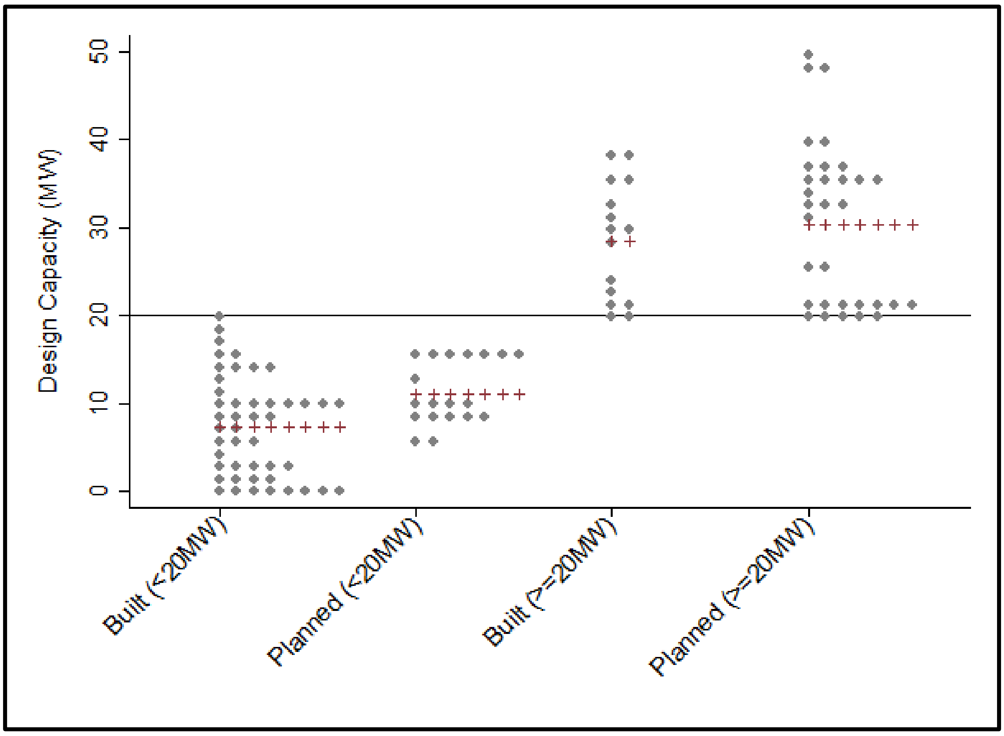


Figure 5.2: Irish Data Centre Market (by development status and EET compatibility)

Source: Author's calculations from Bitpower (2020). Table shows the count of data centres split by development status (Built, Planned) and their capacity. EET compatible threshold of 20MW determined in consultation with MAN.

Analysis considers three types of data centre, based on adoption status (a): 65 facilities that are EET incompatible with an average capacity of 8.52MW ($a = 0$), 15 facilities that are EET compatible but are already built with an average capacity of 29.80 MW ($a = 1$) and 32 facilities that are EET compatible but are planned, with an average capacity of 29.80MW ($a = 2$). Only the latter group adopts the EET.

5.5.4 Power systems model (ENGINE)

EET adoption also has potential benefits to the power system in terms of reduced demand and increased flexibility as storage. This paper performs a power systems analysis to quantify the consequences of EET adoption for the Irish transmission system in the year 2030. ENGINE determines the least-cost optimal generation capacity expansion and operation, subject to technical and policy constraints (D. Z. Fitiwi et al. 2020).

ENGINE has been used to model the consequences of increased interconnection, fossil generation phase out and increased renewable generation and carbon price scenarios by 2030. Results indicate that costs are mainly driven by decommissioning old inefficient generation units. They also find that high renewable targets render carbon price rises ineffective in reducing system emissions (D. Z. Fitiwi et al. 2020).

Finally, Fitiwi & Lynch (2020) consider the spatial effect of data centres on the Irish electricity grid. They find the rise in data centre energy use makes a policy target of reducing emissions more important than a renewable electricity generation target. They note the potential adverse effect on other users from increased transmission system costs from data centres. Table 5 details the parameters used in ENGINE for this study.

Table 5.5: Parameters for ENGINE analysis

Variable	Detail	Reference
Year	2030	(D. Z. Fitiwi et al. 2020)
Carbon Price	€80	Climate Action Plan 2030
RES-E	70%	Climate Action Plan 2030
Scenario		
BAU	Planned fossil fuel phase out and north-south interconnector completed	(D. Z. Fitiwi et al. 2020)
EET	BAU + EET adoption	(D. Z. Fitiwi et al. 2020)

Source: Author's assumptions based on prior literature

5.6 Results

The first set of results quantify the primary benefit resulting from a reduction in data centre energy use due to EET adoption. Following this, the secondary benefit of EET adoption is quantified in terms of hot water supply. Finally, the tertiary benefits of technology adoption on the Irish transmission system in 2030 are presented using a power systems model.

5.6.1 Plant level results

This section details the plant-level model of energy use for each heating end use (H). In the BAU scenario ($H0$) data centre cooling demand is met by mechanical chillers. In all other cases ($H1, H2, H3$), the EET input consumes electricity that is converted to cold water supply which displaces the cold air demand from data centres and supplies hot water for use elsewhere, where EET adoption occurs ($a = 2$). Following Section 5.5.3, annual energy demand is compared for data centres that are too small to adopt ($a = 0$), that are of sufficient scale but already built ($a = 1$) and those eligible to adopt ($a = 2$), across each heating end use scenario (H). Table 6 compares annual energy use for i) IT Input, ii) Grid Cooling iii) EET Input iv) EET Cooling Output and v) EET Heating Output:

i. IT input is the electricity used to power servers. Per Equation 5.2, it is constructed by multiplying the assumed IT electricity use (in MW) by 24 hours by 365 days.
ii. Grid Cooling is the electricity drawn from the grid used for cooling IT hardware for data centres and scenarios ($H0$) where no EET adoption occurs (Equation 5.3). It is the model-based cold duty multiplied by 24 hours by 365 days per year.
iii. EET Input is the electricity required to charge EET, adopted ($H1, H2, H3$).
iv. EET Cooling Output is the amount of cooling for data centres from the EET where adoption occurs ($H1, H2, H3$). It is the model-based cold duty multiplied by 24 hours by 365 days per year. It is treated as deductible.
v. EET Heating Output reflects the energy generated for use as hot water from the EET where adoption occurs ($H1, H2, H3$). It is the model-based hot duty multiplied by 24 hours by 365 days per year. It is treated as deductible.

Table 5.6: Annual plant-level energy balances (MWh)

Scenario	IT Input	Grid Cooling	EET Input	EET Cooling Output	EET Heating Output	Total*
H0: BAU						
a=0 Do Not Adopt (<20MW)	57,412	17,224	N/A	N/A	N/A	**74,636**
a=1 Do Not Adopt (>=20MW)	200,806	60,242	N/A	N/A	N/A	**261,048**
a=2 Adopt (>=20MW)	200,806	60,242	N/A	N/A	N/A	**261,048**
H1: 4GDH						
a=0	57,412	17,224	N/A	N/A	N/A	**74,636**
a=1	200,806	60,242	N/A	N/A	N/A	**261,048**
a=2	200,806	N/A	16,799	(60,242)	(77,831)	**79,532**
H2: 3GDH						
a=0	57,412	17,224	N/A	N/A	N/A	**74,636**
a=1	200,806	60,242	N/A	N/A	N/A	**261,048**
a=2	200,806	N/A	37,746	(60,242)	(101,045)	**77,265**
H3: Industry						
a=0	57,412	17,224	N/A	N/A	N/A	**74,636**
a=1	200,806	60,242	N/A	N/A	N/A	**261,048**
a=2	200,806	N/A	37,698	(60,242)	(101,031)	**77,231**

Source: Author's calculations based on Bitpower (2020) data and MAN parameters. Values in units of Megawatt-hour (MWh) per year. Annual energy use for H0 (Business as Usual) is the sum of IT and Cooling Energy. The total for heating end-uses (H1, H2, H3) is the sum of IT and ETES Input electricity use, minus the Cooling and Heating Output. Values are based on average data centre capacity of 8.52 MW for a=0 and 29.80 MW for a=1,2.

The key result from Table 5.6 is that the plant-level model suggests that EET adoption delivers approximately 70% energy savings in terms of the net energy use, relative to a similar data centre with standard mechanical cooling. This is driven, in large part, by the fact that cooling energy is an input for non-adopting plant and an output of the EET. This is a substantial plant level energy saving. Similarly, EET adoption scenarios feature a substantial level of heat energy as an indirect benefit. Table 5.6 presents the potential savings at an individual plant level (>20MW), the next section explores the market level impacts of these potential savings if the technology is employed in all new eligible data centres.

5.6.2 Market level results

Using input data on upcoming data centre capacity from Bitpower (2020), a ten-year (2019-2028) forecast of market energy use for each Heating End Use is created. This includes existing data centre capacity and new plant that is compatible with EET adoption. Table 5.7 details the market size, split by EET adoption status (additional plant each year in brackets). Appendix 5.C illustrates the same information split by region.

Table 5.7: Data centre market forecast

Year	**Do Not Adopt** $\boldsymbol{a = 0, 1}$	**Adopt** $\boldsymbol{a = 2}$	**Total**
1997-2019	61*	0	**61**
2020	65 (+4)	7 (+7)	**72 (+11)**
2021	70 (+5)	9 (+2)	**79 (+7)**
2022	71 (+1)	12 (+3)	**83 (+4)**
2023	75 (+4)	16 (+4)	**91 (+8)**
2024	76 (+1)	21 (+5)	**97 (+6)**
2025	78 (+2)	27 (+6)	**105 (+8)**
2026	80 (+2)	30 (+3)	**110 (+5)**
2027	80	31 (+1)	**111 (+1)**
2028	80	32 (+1)	**112 (+1)**
Total	**80**	**32**	**112**

Source: Adapted from Bitpower (2020). Note: Values reflect the annual number of data centres, split by EET adoption status. For H0 (Business as Usual), no data centres adopt. Values in brackets reflect the assumed additional data centres in each year. *Of the 61 Do Not Adopt data centres in 2019, 15 facilities are large enough to adopt (> 20MW capacity) but are already built and deemed ineligible. Their energy use is based on the average capacity of 29.80 MW.

Table 5.8 forecasts market energy use (in TWh) using Equations 5.4-5.6 from Section 5.5. The BAU scenario shows sectoral electricity use rising from 7.35 TWh in 2019 to 17.12 TWh in 2028. This reflects the projected market growth from 61 data centres in 2019 to 112 by 2028. Based on the ten-year total energy use, EET adoption would deliver significant energy savings. All EET adoption scenarios ($H1, H2, H3$) would save approximately 26% of energy compared to BAU ($H0$) from 2019-2028. This is significant, especially considering 15 additional data centres are sufficiently large for EET adoption but are not considered since they are already built. These savings emphasise how the additional electricity to power the EET is more than offset by the savings in cooling and heating output.

Table 5.8: Data centre market electricity use

	BAU	EET Adoption		
Year	**H0 Total**	**H1 Total**	**H2 Total**	**H3 Total**
2019	7.35	7.35	7.35	7.35
2020	9.47	8.75	8.90	8.90
2021	10.37	9.44	9.63	9.63
2022	11.23	9.98	10.24	10.23
2023	12.57	10.91	11.25	11.25
2024	13.95	11.77	12.21	12.21
2025	15.67	12.87	13.43	13.43
2026	16.60	13.49	14.12	14.11
2027	16.86	13.65	14.29	14.29
2028	17.12	13.80	14.47	14.47
2019- 2028 Total	131.19	112.01	115.88	115.87
% Difference to BAU		**74%**	**74%**	**74%**
2030 Total	17.12	13.80	14.47	14.47
% Difference to BAU		**19.38%**	**15.46%**	**15.47%**

Note: Author's calculations using data centre capacity information from Bitpower (2020) and MAN EET parameters. Values in TWh. 2030 Total electricity demand in 2030 is reported as identical to 2028. This is because power systems analysis (Section 5.6.3) considers market-level changes in the year 2030.

Table 5.8 masks the specific factors creating savings. The next subsection expands on these results to answer RQ1 and RQ2 by detailing the primary change in energy use for data centre cooling and the secondary change in heating energy use.

5.6.2.1 Market - Direct savings (EET input & cooling)

Figure 5.3 compares 2020 and 2028 market energy use, decomposed by energy source. Net energy use deducts the cooling energy and heating energy where EET adoption occurs. EET cooling and heating output (light blue and green bars, respectively) are considered an output of the EET electrical input, which causes net energy use to fall in each adoption scenario, relative to BAU. Net energy use that is lower than the sum of IT energy use (orange plus yellow bars) and conventional cooling (grey bar) suggests that EET adoption has a positive effect.

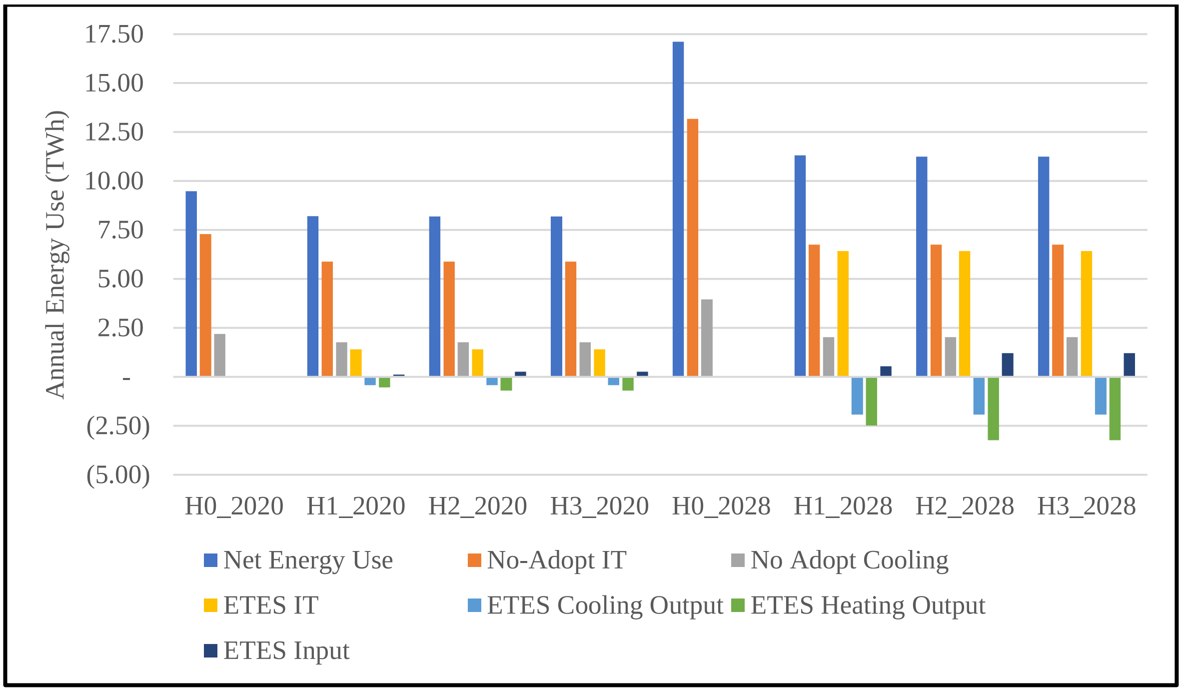


Figure 5.3: Market Level - Net energy use decomposition (2020 v 2028)

Note: Author's calculations based on Bitpower forecast and MAN EET parameters.

The balance between energy displaced by cooling and heating, at the cost of additional electricity used to power the EET determine the level of savings. Per Table 5.9, over the ten-year period from 2019-2028, the electrical EET Input represents between 14% ($H1$) and 31% ($H2, H3$) of the net energy saving delivered by the EET. Cooling output is responsible for between 49% ($H2, H3$) and 50% ($H1$) of the net savings, while heating is responsible for between 64% ($H1$) and 82% ($H2, H3$).

Table 5.9: Comparison of EET-specific energy balance savings

	a **EET Cooling**	**b** **EET Heating**	**c= a + b** **EET Cool + Heat**	**d** **EET Input**	**e = c-d** **Net Energy Saving**
2019-2028 Total Energy Use					
H1	11.14	14.40	25.54	3.11	22.44
H2	11.14	18.69	29.84	6.98	22.86
H3	11.14	18.69	29.84	6.97	22.86
As Fraction of Net Energy Saving (e)					
H1	50%	64%	114%	14%	
H2	49%	82%	131%	31%	
H3	49%	82%	131%	31%	

Note: Based on Bitpower market forecast and MAN EET parameters. Values in TWh.

This result shows that savings in cooling represents roughly half of the net EET savings. The secondary benefit of heating energy requires further investigation in the next subsection to account for network losses. Clearly, EET adoption has a positive effect on lowering electricity demand for data centre cooling, even when factoring in the additional electricity input required.

5.6.2.2 Market - Indirect energy savings (Heating)

Results suggest that EET adoption delivers market-wide savings of 26% over the horizon, with Table 5.9 attributing a substantial share of savings in heating supply. Unfortunately, several factors prevent a full pass-through of this value into effective heating. This section accounts for heat losses associated with transportation from the EET to the supply source.

CODEMA (2018b) notes that there are different heat losses associated with different DH systems. A representative existing DH network in Denmark features annual network heat losses in the range of 38-44%. However, an upgrade to a low-temperature 4th Generation DH system resulted in lower loss levels of 13-14% (CODEMA 2018b). Table 5.10 applies these loss factors for each heating end use to estimate delivered heat savings.

Table 5.10: EET-specific energy balance savings - net of heat distribution losses

	a **EET Cooling**	**b** **EET Heating**	**c = a + b** **EET Cool + Heat**	**d** **EET Input**	**e = c-d** **Net Energy Saving**
2019-2028 Energy Use					
H1 4GDH Market Forecast	11.14	14.40	25.54	3.11	22.44
H1 - Heating network loss (14%)		2.00			
H1 - Net Energy Use	11.14	12.40	23.54	3.11	20.44
H2 - 3GDH Market Forecast	11.14	18.69	29.84	6.98	22.86
H2 - Heating network loss (44%)		8.00			
H2 Net Energy Use	11.14	10.69	21.84	6.98	14.86
H3 - Industrial Market Forecast	11.14	18.69	29.84	6.97	22.86
H3 - Heating network loss (44%)		8.00			
H3 - Net Energy Use	11.14	10.69	21.84	6.97	14.86
H1 Savings (Fraction of Net Energy Saving)	55%	61%	115%	-15%	
H2 Savings (Fraction of Net Energy Saving)	75%	72%	147%	-47%	
H3 Savings (Fraction of Net Energy Saving)	75%	72%	147%	-47%	

Note: Based on Bitpower market forecast and MAN EET technical parameters. Values in TWh. Heating network losses based on case study examples from Codema (2018b).

EET adoption still offers a net energy saving after accounting for heating network losses. Savings are least affected in $H1$, where a low-temperature 4th Generation DH network connects to energy efficient buildings. In $H1$, heating energy accounts for 61% of net energy savings, compared to 64% with no distribution loss applied.

Savings are lower for a higher-temperature 3rd Generation DH network that supplies less energy efficient buildings, accounting for 72% of net energy savings when accounting for distribution losses, compared to 82% of net energy savings with no distribution losses. In this study, $H3$ is quantitatively identical to $H2$. However, it is possible that additional savings may be attainable by locating the industrial use adjacent to the EET.

5.6.3 Tertiary savings for national transmission network

As detailed in Section 5.5.4, this study uses the ENGINE model to quantify the consequences of EET adoption on the Irish transmission system in the year 2030. Results compare a benchmark BAU case with a scenario of EET adoption following $H1$. The power systems model does not quantify changes in heating energy use, so only one adoption scenario is considered.

It assumes 1954 MW of data centre capacity installed by 2030, with an additional 424 MW attributed to the EET installations. ENGINE determines the least-cost pathway assuming that data centres can be powered either by the EET or conventionally cooled from grid-sourced electricity. To account for possible cooling losses, the optimization includes a conservative 20% overhead for cooling load beyond the required level.

Table 5.11 lists the anonymised regions of EET installations, including EET capacity and the level of cooling demand for data centres. The least-cost scenario highlights significant regional heterogeneity in EET capacity and notes that data centres are cooled by the EET roughly half of the time. This presents an argument for conventional grid-powered cooling infrastructure in addition to EET, although there is no consideration of the additional capital cost involved. During these times, the EET serves more valuable functions to the grid.

Table 5.11: EET capacity and data centre cooling demand (2030)

Site ID (Anonymised)	EET Capacity (MW)	Cooling demand (TWh)		
		Direct	ETES	Total
1	15.67	0.035	0.031	0.066
2	26.44	0.057	0.054	0.110
3	94.01	0.183	0.190	0.372
4	68.54	0.148	0.141	0.289
5	13.71	0.030	0.027	0.057
6	6.85	0.015	0.013	0.029
7	104.80	0.220	0.219	0.439
8	55.83	0.121	0.115	0.235
9	31.34	0.067	0.065	0.132
10	6.85	0.015	0.014	0.029
Total	**424.04**	**0.891**	**0.869**	**1.758**

Source: Results based on ENGINE 2030 simulation.

A public benefit of EET adoption is its storage function. Table 5.12 illustrates the change in capacity expansion to meet the 70% RES-E target. Adding 424 MW of EET adoption displaces 1,074 MW of planned generation capacity, while meeting the 70% RES-E target. Reductions are observed for Battery Storage (596 MW), Solar PV (536 MW) and Offshore Wind (365 MW). This represents substantial savings from the network planner perspective, especially considering additional issues such as local opposition to renewable generation.

Table 5.12: Comparison of renewable generation expansion (2030)

Variable	2030 BAU (MW)	2030 EET (MW)	Difference	Difference %
Onshore Wind	5206	5206	- 3.40e-06	- 6.53e-08
Solar PV	3445	2783	- 536	- 15.57
Offshore Wind	3148	2783	- 365	- 11.60
Battery Storage	3717	3121	- 596	- 16.03
ETES EET	0	424	+ 424	
Total	**15,516**	**14,443**	**1,074**	- 6.92

Source: Results based on ENGINE 2030 simulation.

Finally, ENGINE quantifies the difference in costs between scenarios (Table 5.13). The headline result is that EET adoption leads to an 8.64% reduction in operating and capital costs in term of net present value, before accounting for EET capital costs. There is also a 2.76% reduction in system-wide emissions and a near-total reduction in costs associated with maintaining grid reliability. This is eliminated because the EET serves as electricity storage.

Table 5.13: Comparison of system-wide costs (2030)

Variable	2030 BAU	2030 EET Adoption	Difference	Difference %
Net Present Value (OP & Cap) (M€)	1613.39	1473.93	- 139.643	- 8.64
Emissions ($MtCO_2$)	9.58	9.319	- 0.264	- 2.76
Grid Investment Needs (M€)	624.69	533.7758	- 90.91	- 14.55
Reliability Cost (M€)	25.77	8.11e-07	- 25.76	- 99.99
Emission Cost (M€)	318.15	309.38	- 8.77	- 2.76
Energy Cost (M€)	644.80	630.78	- 14.01	- 2.17

Source: Results based on ENGINE 2030 simulation.

In summary, power systems analysis shows promising benefits for the national grid associated with EET adoption. Overall, EET adoption leads to an 8.64% reduction in operating and capital costs in term of net present value. Importantly, this value does not include information on the capital cost of EET adoption or any heating network infrastructure (Section 5.6.2) but serve as a helpful threshold value when considering societal benefits associated with EET adoption.

5.7 Concluding remarks

The EU has set targets for increasing renewable generation, lowering emissions and fostering energy efficiency (European Commission 2019a). However, countries are free to decide how their goals are met. Ireland is a prime example of a country with success in intermittent renewable generation but with little progress in decarbonising heating. At the same time, Ireland is acutely affected by an expected surge in capacity from data centres (EirGrid 2019). The electricity-reliant nature of data centres paired with their spatial concentration pose unique questions for Ireland. It is imperative that policymakers leave no stone unturned in the search for energy efficiency technologies (EETs) that help to address these challenges, especially for solutions that foster energy systems integration across sectors.

This paper quantifies the key economic benefits associated with technology adoption that is designed to supply cold water for data centres, hot water for a district heating network and grid storage to facilitate greater penetration of renewable electricity generation sources. The technology considered is the MAN electro-thermal energy storage (ETES) system, which can meet these objectives and foster sector coupling.

Pairing a unique plant-level forecast of data centre capacity in Ireland with technical parameters on the EET, this study quantifies i) the change in electricity demand associated with technology adoption ii) the hot water energy to use as supply to a potential district heating network and iii) a power-systems analysis of grid-level effects of technology adoption in the year 2030, subject to policy constraints.

The first result suggests that technology adoption could help to reduce national electricity demand by 26%, over the period 2019-2028. This is driven by EET adoption that converts electricity into cooling energy, which can be displace grid-powered cooling in data centres. The second result suggests that technology adoption could supply 12.40 TWh of hot water for use in a 4th Generation district heating network. For Ireland, the lack of established district heating presents an opportunity to using the latest, most efficient technology.

Finally, a power systems analysis in the year 2030 suggests that EET adoption can reduce system costs by 8.6%, albeit without accounting for the capital cost of the EET. This result includes a 6.92% reduction in additional RES capacity, as the EET provides grid storage. There is also a 3% reduction in emissions, without including savings associated with displacing fossil fuel-based heating with hot water supply.

There are two notable limitations to this study. First, the true energy savings of EET adoption may be overstated due to the assumption that facilities are cooled by chilled air in the reference case, with a 30 per cent overhead on assumed IT load. Some data centres might plan to use ambient air cooling, which features a lower cooling overhead. However, the lack of private plant-level information, combined with trends in rising server density that are likely to require more advanced cooling techniques make these assumptions reasonable.

The second limitation is the lack of information regarding additional capital costs associated with data centre adaptation, EET and heating end-use construction. A formal cost-benefit analysis would be heavily influenced by the capital costs of investment. The lack of plant-level costings prevents such an exercise. Instead, this paper is concerned with quantifying the amount and value of energy balances, with a power systems analysis of a threshold value of additional grid investment in 2030.

The increasing demand for data centres paired with increased policymaker focus on energy efficiency justify the assumptions. Future work involving collaboration between relevant stakeholders could address this knowledge gap. The significant opportunity for decarbonisation outlined in this study warrants consideration of ways to foster this collaboration. In Ireland, pilot schemes for district heating have featured collaboration between city councils, a project partner and a private data centre (CODEMA 2018a). The important role of the national electricity grid suggests there is an opportunity for EirGrid, the Irish transmission system operator (TSO) to facilitate collaboration between public (government departments, county councils) and private (data centres, technology providers) stakeholders. This would be appropriate, since EirGrid already liaises with many data centres during the planning and construction phase. The scale and ambition of any such initiative may require a national authority, beyond the county council level.

This paper highlights the multiple benefits associated with EET adoption to foster increased cooperation between different energy stakeholders. Although policymakers value the ability to store intermittent renewables and to supply a district heating network, they may not value cold-water supply for data centres. Asymmetric information and objectives may constitute a market failure where EET adoption may not occur. This study quantifies many of the benefits that could be achieved through policies that spur EET adoption.

5.A IDA Ireland (2018) Economic Contribution

Section 5.3 highlights the significant presence of data centres in Ireland and how this is expected to develop over time. This appendix details efforts to quantify the economic contribution of sixteen firms with data centre operations in Ireland (IDA Ireland, 2018). Estimates of economic contribution is derived from direct investments and indirect economic activity, per national Input-Output table multipliers. Construction investment since 2010 at €4.64bn, of which €2.96bn is direct and a further €1.68bn is indirect benefit. The contribution from operations is valued at €2.49, of which €1.59bn is direct and €0.90bn is indirect. The report also reports employment value of 5,700 full-time equivalent positions, with 2,900 construction-related jobs (1,000 of which are indirect) and 2,800 workers (1,000) of which are indirect) employed as part of operations.

IDA notes the contribution of companies with data centres in other sectors (IDA, 2018). Since 2010, companies with a large data centre investment in Ireland have doubled their employment from over 4,000 to almost 10,000 since 2010. Firms view their Irish data centre presence as strategically linked to their overall operations in Ireland. Further qualitative benefits include collaboration on higher level education courses and the exportability of skilled Irish data centre suppliers to other countries. A 2016 survey by the Irish Construction Industry Federation noted that Irish companies were involved in projects abroad with a capital value of over €2.2bn, with a direct employment of 6,600 full-time Irish jobs (IDA, 2018).

5.B MAN ETES technology information

The ETES system is based on a closed loop where CO_2 is compressed with the resulting heat and cold being stored. During the charging cycle (Figure 5.4, left panel), electricity is converted into heat and cold and stored in isolated tanks. During the discharging cycle (Figure 5.4, right panel), the reverse occurs. MAN estimates that the round-trip grid-to grid efficiency of this process reaches approximately 50–55%. The use and distribution of heat or cold from the thermal storage increases the overall system efficiency up to 70%.

Charging Cycle **Discharge Cycle**

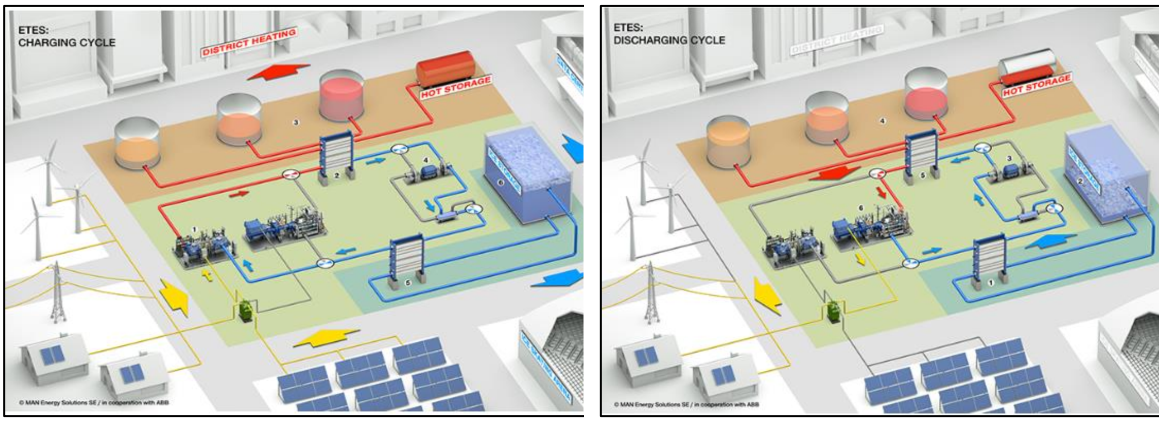


Figure 5.4: [5A] MAN ETES system description

Source: MAN Energy Solutions. https://www.man-es.com/discover/a-tale-of-fire-and-ice

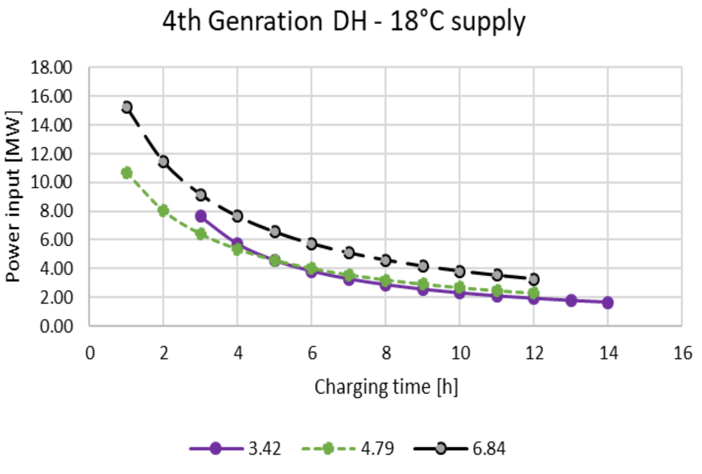
The Charging Cycle

- When intermittent renewables are generating surplus energy, this surplus energy is used to power a CO_2 compressor, which heats it to 120°C. This compressed CO_2 is fed into a heat exchanger and used to heat water.
- The hot water is stored in isolated tanks of varying pressure and temperature. In the base case there are four tanks, three atmospheric and one pressurized. This hot water is used as a source for district heating demand.
- The high-pressure CO_2 is then fed into an expander, which lowers the pressure of CO_2 while also liquefying and cooling. This liquefied CO_2 is then pumped through a second heat exchange system. However, this is performed on the cold side of the heat exchanger system.
- The heat taken from the surrounding water and an ice storage tank is formed and maintained. This is used as an input in data centre cooling.

The Discharging Cycle

- CO_2 gas enters the heat exchanger on the cold side of the system and it condenses due to the cold originating from the ice storage tank. This melts the ice in the ice storage tank.
- A CO_2 pump is used to increase the pressure of the CO_2 pump again.
- The pressurised CO_2 then passes through a heat exchanger and is heated by the water that is in the hot water storage tank.

  The heat from the heated CO_2 is fed into a power turbine and is converted back into electricity via a coupled generator. This electricity is then provided to the grid and delivered to consumers during times of low generation.



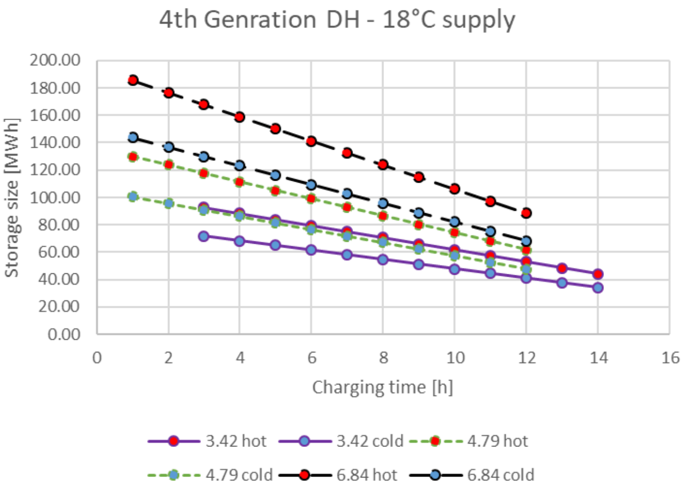


Figure 5.5: [5B] MAN ETES power input and storage size by charging time

Source: MAN Energy Solutions. https://www.man-es.com/discover/a-tale-of-fire-and-ice

5.C Regional summary of EET compatibility

This appendix provides a regional breakdown of data centre rollout and EET compatibility, which is presented nationally in the body. Figure 5.6 illustrates the regional frequency of data centres. Blue bars reflect data centres that are built, while red bars reflect upcoming data centres. Technical guidance determined that data centres under 20MW are not suitable for adoption due to economies of scale. Results impose technology adoption only on the planned data centres that are of sufficient scale, represented by red bars above the threshold.

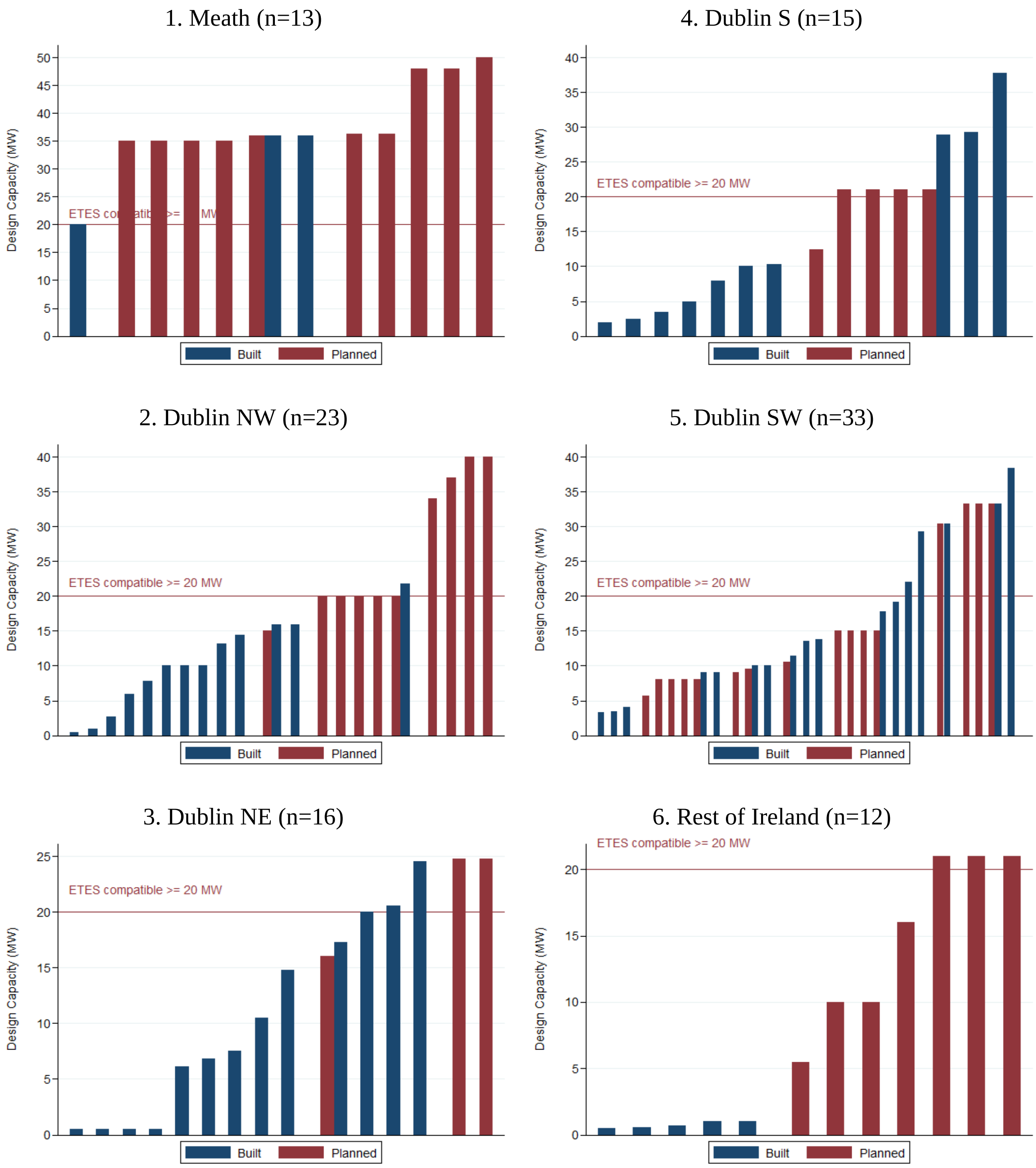


Figure 5.6: [5C] Data centre capacity - by region (in 2028) and development status

Source: Bitpower market data with threshold value of 20 MW informed by MAN.

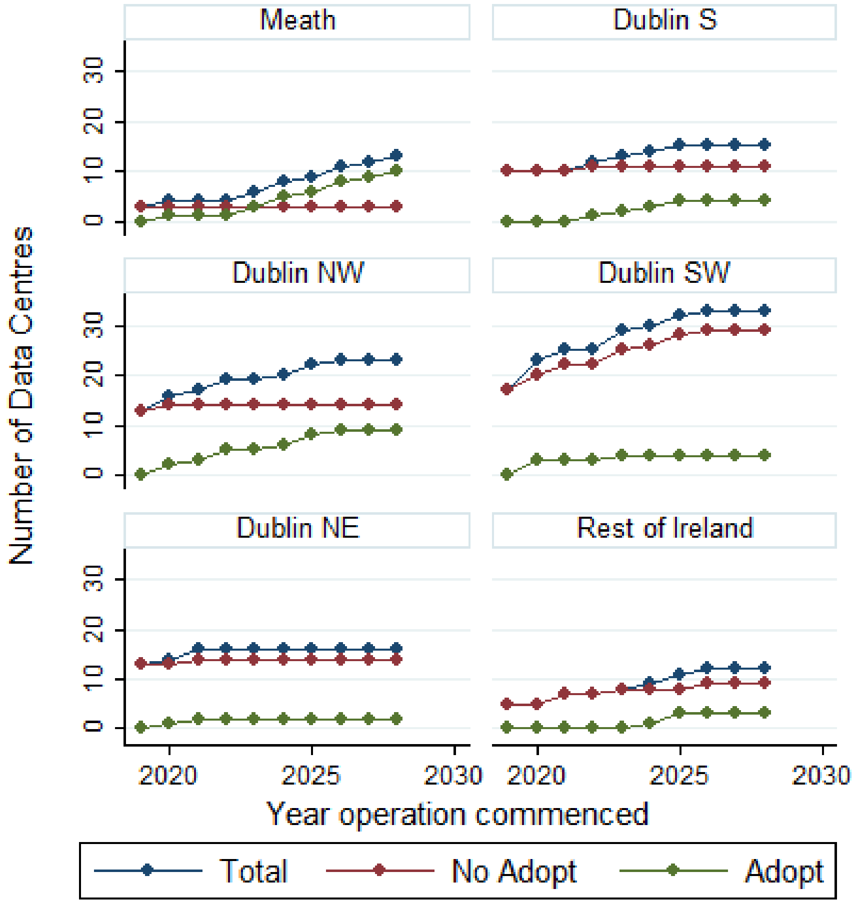


Figure 5.7: [5D] Market adoption (by region)

Source: Adapted from Bitpower (2020). Note: Values reflect the annual number of data centres, split by EET adoption status. For H0 (Business as Usual), no data centres adopt. Values in brackets reflect the assumed additional annual data centres in each year.

Chapter 6: Conclusion

This thesis identifies several areas where energy efficiency has promise in both the residential and commercial data centre sectors. It represents an important step in helping to understand the real benefits of energy efficiency policies across a variety of sectors. It emphasises the value of presenting accurate information through labelling policies and by correctly calibrating subsidies to improve energy efficiency and lower energy demand. It also quantifies the scope for improving energy efficiency in a key emerging, yet uncertain industry and highlights the multiple benefits to society associated with technology adoption.

6.1 Key Findings

This thesis provides a valuable contribution by studying the residential and commercial data centre sectors. Although each chapter focuses on one particular area or policy, the collective results are worth taking as a whole. The key findings are summarised as follows:

1. **EPCs are an imperfect benchmark**

Energy Performance Certificates serve a useful purpose as a source of information on dwelling energy efficiency. However, recent years have seen them used to underpin targets to decarbonise the residential sector. Chapter 2 tested for the existence of an Energy Performance Gap between theoretical and actual energy use in a sample of Irish dwellings and found significant heterogeneity across the entire EPC spectrum. The most efficient houses consumed more energy than expected while the least efficient demonstrated significantly less energy consumption than expected by the EPC.

2. **Residential retrofit policies may disappoint**

Chapter 3 studies the effectiveness of a national subsidy scheme, finding an average reduction in energy use associated with a retrofit after controlling for household and time fixed effects (average of 943 kWh/year). The strongest result is that a retrofit of just a gas boiler upgrade is associated with a significant reduction in energy demand (average of 1,027 kWh/year). However, these results mask additional evidence suggesting there is a significant increase in energy use for almost half of the combinations of retrofit.

As the attention of policymakers move towards 'deeper' retrofits featuring many retrofit measures, this work suggests that caution must be taken to ensure retrofits will deliver value for money. On this point, Chapter 3 suggests that retrofits are currently less appealing (on the basis of net upfront cost per kilowatt-hour per year) to households, as the expected change in EPC due to retrofit is smaller than the actual change observed.

3. Residential energy demand is relatively inelastic

Chapters 2 and 3 demonstrate actual energy use deviating from the EPC-expected level. However, there is a striking lack of variation in average actual energy use observed. In Chapter 3, the 15-grade EPC features a high positive correlation with average bimonthly energy use (0.96). However, there is a far lower correlation between average actual bimonthly energy use and the same EPC (-0.14). In Chapter 2, the largest difference in average actual energy use is only 457 kWh/year between E-rated homes and AB-rated homes. The average difference for the same EPC bands is 10,562 kWh/year.

Taken together, this thesis suggests that energy use does not vary by nearly as much as the EPC suggests. In this sense, EPCs fall short in being an appropriate yardstick for policymaking. Estimates suggest that a policy to retrofit 500,000 Irish homes by 2030 to B2 standard (Government of Ireland 2019) may cost €50 billion (Farry 2019). This work shows why a more accurate picture of residential energy demand is required to diagnose appropriate needs and to target subsidies towards proven measures.

Such a broad policy runs the risk of greatly improving dwelling energy efficiency while not changing (or even increasing) energy use. In practice, reaching a standard of energy efficiency may be easier than achieving a set reduction in energy use. However, this study is cognizant of the additional benefits of retrofit, including transitioning to lower carbon fuel sources and realising the non-monetary benefits of retrofit, which have been found to be especially important for the most vulnerable in society (Coyne et al. 2018).

4. New industries represent significant decarbonisation opportunities

Chapters 4 and 5 highlight the issues policymakers face when trying to chart a course towards a low carbon future. In particular, plans made in the past may fail to account for the emergence of an entire industry that has an outsized impact on energy use at the national level. Both chapters are interested in the rise of data centres as a major source of electricity demand in Ireland and how this is expected to continue into the future. As data centres have become a vital part of the digital economy, their presence and energy use has real consequences for country-level energy use.

Chapter 4 shows that data centres have the potential to contribute to helping reach the low-carbon future by engaging with energy efficiency. If every data centre expected to be built in Ireland could fully abate the energy which is used for server cooling, it would translate to saving 2.93 TWh each year from 2028 onwards (39.57 TWh/year). For context, retrofitting 500,000 homes using the average annual saving of 943 kWh/year in Chapter 3 leads to an annual saving of 0.4175 TWh/year.

Extended to the ideal policymaker scenario, a national dwelling stock of 2,000,000 households at B2 EPC standard would be expected to consume 15.06 TWh/year, based on the average theoretical energy use for the sample considered in Chapter 3 (7,530 per dwelling each year). This disparity serves to highlight the significant untapped potential in the industrial sector. However, the level of asymmetric information regarding current data centre technologies has the potential to limit the extent to which policymakers could spur energy efficiency in the sector through policies. It is argued that the benefits of reduced emissions accrue to all of society, not just firms. As such, there could be merit in a policy that could foster greater awareness and engagement with energy efficiency.

5. Great potential for decarbonisation through cross-sector collaboration

Chapter 5 quantifies the multiple benefits associated with the adoption of energy efficiency technology that is designed to supply cold water for data centres, hot water for a potential district heating network and grid storage to facilitate greater penetration of renewable electricity sources. Chapter 5 quantifies i) the change in electricity demand associated with technology adoption ii) the hot water energy to use as supply to a potential district heating network and iii) a power-systems analysis of grid-level effects of technology adoption in the year 2030, subject to policy constraints. Aside from the savings for data centre electricity demand for cooling, technology adoption would provide substantial hot water for use as part of a district heating network (12.40 TWh/year).

Technology adoption could help to reduce investment costs on the national electricity grid in the year 2030 by 8.6% or €139 million in NPV terms. It could help to reduce electricity generation capacity expansion (by 1,074 MW), facilitate greater system-level reliability and storage that can allow a higher penetration of intermittent renewable electricity. It would also lower the cost of energy by 2.17%.

All of the discussed benefits do not accrue to the owner of the energy efficiency technology. This may help to explain, in part, why such technology has not been adopted widely to date. The results in Chapter 5 show the significant benefits for other sectors of the economy associated with technology adoption. Such a public good is certainly deserving of serious consideration by policymakers in their efforts towards reaching a low-carbon future.

6.2 Future Research

A number of promising avenues for further research have been identified, based on the findings and limitations within each chapter. These open questions have been highlighted as important areas for future work to address. These areas include the following:

1. **Improving residential EPCs**

Chapters 2 and 3 highlight the valuable role of EPCs as an imperfect source of information regarding dwelling energy efficiency. Results identified significant variation in the extent to which actual energy use deviated from the level expected by the EPC. The increased adoption of smart home energy meters represents a rich new source of data on occupant behaviour which could help create a better EPC. Further work could seek to exploit this real-time data to better understand consumer behaviour patterns. Up to now, evidence has been limited to trials (Di Cosmo et al. 2014; Harold et al. 2018).

The importance of this data has been recognised at government level, with ambition to have full adoption of smart meters in the coming years to improve information and unlock potential for demand side management (Government of Ireland 2019). There is untapped potential in collating a national database of residential energy use across utilities. This platform would accommodate consumer switching between utilities and would provide a dwelling-specific measure of actual energy use that could be used to inform the construction of the EPC or to provide an extra data point to consumers. It would better reflect whole-home energy use by accommodating consumers with electricity and heating from different utilities. The increasing use of heat pumps and natural gas will help to further reduce the extent to which unmetered fuels (oil, solid fuel) drive missingness in the data.

2. **Calibrate retrofit subsidies to reflect ex-post analysis**

Chapter 3 highlights the significant variation in occupant energy use after receiving a retrofit. It shows how almost every combination of measures improves dwelling energy efficiency, with some combinations leading to reduced energy use while others lead to higher energy use. This study highlights the importance of ensuring that subsidy levels are appropriately designed to reflect actual reductions in energy use.

One way to accurately calibrate subsidy levels is to monitor dwelling energy use pre- and post-retrofit. The real savings observed would show the actual effect of certain measures, while accounting for household-specific behaviour. Currently, recipients of a retrofit only receive a visual inspection that the work was completed, with no ex-post billing data analysis. Chapter 3 shows that observing energy use in dwellings is important to understand the benefit of retrofit, given that the main justification of such subsidies is to lower energy use and to work towards national climate targets. This would serve to improve the retrofit subsidy scheme by reallocating resources towards the most effective measures.

3. **Establish a scheme to promote energy efficiency collaboration with large industry**

Chapter 4 highlights the significant energy demand of large firms (with the example of data centres) and the great uncertainty that their presence can place on network planners and policymakers. The private nature of firms makes it difficult to understand current efforts towards energy efficiency and future plans for growth. This thesis proposes that a publicly available database of the sector that outlines current and future plans for energy efficiency would be a valuable resource. An example of such a voluntary scheme, like the EU Code of Conduct for Data Centre Energy Efficiency (European Commission, 2016), has been associated with improvements in data centre energy use (Avgerinou et al., 2017).

If such a scheme featured the entire industry, it would have multiple benefits. Firstly, it would provide an accurate understanding on the true contribution of firms towards national energy demand, which is often poorly viewed (Lillington 2016). Secondly, it would introduce a competitive aspect to help motivate firms to improve energy efficiency. This would serve as a healthy form of competition where society benefits - an example of this is the Greenpeace ranking of green tech firms (Greenpeace 2017). Finally, improved information would reduce uncertainty and allow policymakers to design supports that would help to improve overall welfare.

4. Investigate further opportunities for energy systems integration

Chapter 5 studies the significant energy savings that can be achieved by large-scale energy efficiency technology. As noted earlier, this could prove to be a fruitful avenue for policymakers to achieve savings across the residential sector, commercial operators and for the national grid infrastructure simultaneously. However, this is limited due to the historical lack of collaboration between public and private stakeholders, often due to differences in discount rates (see Solow (1963), Arrow & Lind(1978)).

For policymakers, Chapter 5 outlines the benefit of policymakers serving as a matchmaker for private sector innovations (such as the one examined) and schemes which could help to improve societal welfare. At a minimum, such a platform would help to improve information. In theory, it could lead to the realisation of large-scale innovations which could benefit society, by facilitating greater use of renewable electricity and by serving as a source of low-carbon heating for households and firms.

Results in Chapter 5 are limited by the uncertainty surrounding district heating networks in Ireland, which makes a cost-benefit analysis difficult to perform. Fortunately, pilot schemes are ongoing to provide district heating in Ireland (Government of Ireland 2019), which has been made possible by recent advances in technology. Future work should look to incorporate this data to understand the benefits of a district heating network in Ireland.

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