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Empirical Essays on Consumer Engagement and Heterogeneity in Residential Energy Demand

A Thesis Submitted in Application for the Degree of Doctor of Philosophy
to the J.E. Cairnes School of Business and Economics
at the National University of Ireland, Galway

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National University *of* Ireland, Galway
Ollscoil na hÉireann, Gaillimh

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Declaration

I declare that this thesis, submitted to the National University of Ireland, Galway for the degree of Doctor of Philosophy (Ph.D.), has not been submitted as an exercise for a degree at this or any other university. All research contained herewith is entirely my own and the use of all material from other sources has been properly and fully acknowledged.

Jason Harold

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Abbreviations

2SLAD	Two Stage Least Absolute Deviations
2SLS	Two Stage Least Squares
AIDS	Almost Ideal Demand System
ATE	Average Treatment Effect
CATI	Computer Assisted Telephone Interviewing
CER	Commission for Energy Regulation
CES	Chief Economic Supporter
CMMS	Consumer Market Monitoring Survey
CPI	Consumer Price Index
DSM	Demand Side Management
ETS	Emission Trading Scheme
EU	European Union
FE	Fixed Effects
FES	Family Expenditure Survey
HBS	Household Budget Survey
HTE	Heterogeneous Treatment Effect
IHD	In-House Display
LAD	Least Absolute Deviations
LPG	Liquefied Petroleum Gas
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
SEAI	Sustainable Energy Authority of Ireland
PIN	Personal Identification Number
QTE	Quantile Treatment Effect
UK	United Kingdom
VCWG	Vulnerable Consumers Working Group

Abstract

Residential energy demand is a key priority area for energy policy in the European Union, especially for the engagement of its citizens in a so-called 'Energy Union' that encourages consumers to take ownership of the energy transition to a low carbon economy. Consumers can engage in energy markets in several ways and there can be significant differences in the nature and depth of this engagement amongst individuals and households. More generally, variations in the demand for energy and in the energy related behaviour of households are also important for policy. In this context, the objective of this thesis is to examine issues relating to consumer engagement and heterogeneity in residential energy demand. It addresses four specific goals aligned with this objective in four separate empirical essays.

A better understanding of the determinants of residential gas demand can support the development of policy measures intended to engage consumers and change aspects of their behaviour relating to household gas use. This information is particularly important when designing demand side management (DSM) programmes which encourage households to play a more active role in managing their energy use. Thus, the first essay of this thesis examines the determinants of residential gas demand using a random effects model of daily gas consumption panel data from a large scale smart metering trial in Ireland. It analyses the effects of the socio-economic and dwelling characteristics of households, as well as the impact of weather-related variables, on residential gas use. In addition, the analysis employs a quasi-experimental methodology, through difference-in-differences estimation, to identify the effectiveness of DSM in engaging households to reduce their gas consumption.

To help realise the full potential of DSM, the second essay of this thesis explores the heterogeneous effects of DSM on residential gas demand across different groups of households categorised by their socio-economic, household level and dwelling characteristics. A random effects model is utilised where the average treatment effects are allowed to vary systematically across the different characteristics to determine which household

factors are more or less responsive to the programme. In addition, a fixed effects model is employed where the overall effect is allowed to vary across billing cycles to establish if DSM programmes induce habit formation in households, while a quantile regression model is employed to explore the variability in effects across the distribution of daily gas consumption.

The elasticity at mean income is usually the parameter of most interest when examining the relationship between energy expenditure and income. However, not all policy is concerned with the average household and is more likely to target low or high energy consumption households. To this end, the third essay examines the variation in the income elasticity of household energy demand across the distribution of energy expenditure. The analysis is based on the application of a two stage instrumental variable quantile regression methodology to five independent cross-sections and the pooled sample of the Irish Household Budget Survey (HBS) to estimate elasticities across the distribution of energy expenditure. The elasticities are compared across high and low energy consumption profiles and to the benchmark constant mean elasticity estimated separately using a two stage least squares method.

Consumer switching is understood to play a key role in creating competitive markets and it is important that consumers actively engage in switching to help maintain competitive pressure on energy providers. Using a pooled cross-section from a pan-European market monitoring survey, the fourth essay explores the role of consumers' socio-demographic characteristics, together with their attitudes to the main features of the market, on the propensity to switch in energy markets across Europe. The analysis estimates a binary logit model for overall switching across 14 European markets, as well as separate models for switching in both the electricity and natural gas markets for comparison. In an extension to the analysis, another model is considered to provide evidence on whether switching in other non-energy markets influences switching in energy markets, while finally, separate country models are estimated to compare the heterogeneous effects of the different influential factors on switching across countries.

For my parents Martin and Jude, my wife Michelle and our daughter Clara.

Chapter 1

Introduction

1.1 Context

Residential energy demand represents a significant share of overall energy consumption, accounting for a quarter of total energy consumption in the European Union (EU) (European Commission, 2016). As a consequence, it is a key priority area for EU policymakers concerned with the engagement of its citizens in a so-called 'Energy Union' that encourages consumers to take ownership of the energy transition to a low carbon and climate friendly European economy (European Commission, 2015b). The Energy Union endeavours to make energy more secure, affordable and sustainable by facilitating the free flow of energy and energy services across EU Member States. Indeed, the vision of the Energy Union set out by the European Commission is one where energy consumers "benefit from new technologies to reduce their bills, participate actively in the market, and where vulnerable consumers are protected" (European Commission, 2015b). Thus, an effective Energy Union requires the active engagement of its residential consumers in the energy market.

Consumer engagement is important for a number of reasons. It results in informed consumers who have greater awareness of their energy use and an improved capacity to change their consumption behaviour to be more energy efficient and sustainable. It leads to more competitive energy markets where there is a better choice of services and suppliers, and switching between them is convenient. It also helps protect consumers, especially those vulnerable to energy poverty, by making energy use and costs more transparent and, overall, it can contribute to consumer welfare.

There are several ways residential energy consumers can engage in the market. For example, engagement can occur through the energy consumer's interaction with accessible, transparent, and comparable consumption information to aid their decision

on how much energy to use and help avoid unnecessary costs. Another way engagement transpires is through consumer switching, where consumers can search for the best alternative energy service and then switch to their preferred choice. In fact, consumers could become more empowered to engage in energy markets by enhanced regulatory and social policies.

Given the EU's commitment to support the rollout of electricity and natural gas smart meters across Member States (European Commission, 2014), these smart technologies offer new ways to help consumers further engage in the energy market and take control of their household energy consumption and costs. Such technologies allow a more widespread implementation of so-called demand side management (DSM) programmes, which work by providing energy saving information to consumers or by giving financial incentives to reduce consumption. To date, DSM programmes have been found to be quite effective in engaging domestic consumers (Goulden et al., 2014) and also in reducing household energy use (Faruqui et al., 2010).

Another important issue relating to consumer engagement is the protection and empowerment of vulnerable consumers. As part of the EU's drive to promote engagement in energy markets, the European Commission launched the Vulnerable Consumer Working Group (VCWG). Discussions in the VCWG identified vulnerable consumers as those who require particular support and assistance for engagement in the successful transformation of EU energy markets (VCWG, 2013). Appropriate engagement could help ensure vulnerable households benefit from the best deals and fairest energy tariffs, like any other consumer. Social policy mechanisms, primarily through the provision of income supports, are commonly used throughout the EU to protect vulnerable consumers and help alleviate some of the causes of disengagement.

'Delivering A New Deal for Energy Consumers', as set out in the EU's Energy Union Strategy, places consumers at the heart of a functioning energy system (European Commission, 2015b). The 'New Deal' requires the further adaptation of current national regulatory frameworks to help motivate EU energy consumers to become more active. It emphasises that switching supplier or energy contract is an important action for consumers participating in energy markets. Despite this, switching rates across European countries are remarkably low and are a constraint on the competitive outcomes envisaged for the Energy Union. There is a concern that consumers who could potentially benefit from switching do not have the adequate resources or information to fully engage in the markets. To ensure engagement, factors involved in consumer switching need to be understood so that switching can be made more straightforward and uncomplicated (European Commission, 2015a).

While consumer engagement is crucial to an Energy Union and residential energy consumers can engage in several different forms, there can be substantial differences in the nature and depth of such engagement amongst individuals and households. In his Nobel lecture, Heckman (2001) suggests that the most important discovery to emerge from micro-econometric investigations is "the pervasiveness of heterogeneity and diversity in economic life". He states that when taking into account heterogeneity in responses, the edifice of the representative consumer is found to lack empirical support. Policymakers and regulators tend to benefit significantly from a real understanding of this heterogeneity in consumer engagement, since it can help them implement more targeted policy and regulatory measures which ultimately lead to more efficient outcomes in energy markets.

As well as heterogeneity in engagement, there are policy-relevant variations in the demand for energy and in the energy related behaviour of households more generally. In particular, an understanding of how a household's domestic energy use is linked to its individual and household level characteristics, and to the structural and energy efficiency characteristics of its dwelling, is relevant for policies to reduce energy consumption. Moreover, recognising heterogeneity in the income elasticity of household energy demand is important for assessing the true impacts of policies such as income supports and/or environmental taxes on household energy use. For energy demand, heterogeneity around the choice of, and preference for, an energy commodity can be even more complex since it is a derived demand. This is because energy itself is not directly consumed by an individual or household but instead derived from the demand for the services it is used to produce e.g. the demand for natural gas for space and water heating.

Within this broad context, this thesis investigates issues relating to consumer engagement and heterogeneity in residential energy demand. Specifically, it examines the determinants of residential gas demand to provide policymakers with a better understanding of the factors affecting household gas demand when designing effective policy measures to engage consumers and encourage energy conservation. Additionally, this thesis identifies the impact of a DSM programme on household gas demand and estimates the heterogeneity and habit formation in the programme's overall effect. Furthermore, it explores heterogeneity in the income elasticity of household energy demand across the energy expenditure distribution to show that households at different consumption levels have differing elasticities, to a large enough extent to make a difference for policy. Finally, it examines consumer engagement through switching by analysing the differences in the factors influencing consumer switching in energy

markets across Europe.

The empirical studies in this thesis rely on individual/household-level data drawn from two geographical areas: national level (specifically from Ireland) and European level. Chapters 2, 3 and 4 use data from Ireland. The topics in these chapters require data with as much detail as possible about individual and household characteristics, while temporal variation is also important. This level of detail tends only to be available in single country sources. When assessing the likely costs and benefits of smart metering for gas and electricity, Ireland carried out a large-scale behaviour and technical trial, yielding unusually good micro-data on consumer behaviour, which is especially useful for the empirical analyses in Chapters 2 and 3. Ireland has also collected several waves of micro-data appropriate for the empirical work in Chapter 4 and it has a history of related analyses upon which this new research can build. Turning to the empirical work in Chapter 5, differences in national markets and institutional conditions are helpful in identifying the main factors associated with consumer switching. A multi-country dataset is employed for this analysis.

1.2 Research Objectives

The overall objective of this thesis is to examine issues relating to consumer engagement and heterogeneity in residential energy demand. The thesis has four specific goals, which are addressed in four separate empirical essays. More specifically, the thesis aims to analyse and explain:

1. The determinants of residential gas demand in Ireland;
    - Are the socio-economic characteristics of the household, together with the energy efficiency of the dwelling and weather-related variables, important factors for residential gas demand?
    - Are there significant differences in gas demand across households?
    - Did the DSM programme employed in Ireland's Smart Metering Gas Consumer Behavioural Trial engage households to reduce their daily gas consumption?
2. Heterogeneity and habit formation in the effect of DSM stimuli on residential gas consumption;
    - Are there differences across groups of households in the average treatment effect on household gas usage from participation in a DSM programme?

- Is the change in household gas consumption behaviour from participation in a DSM programme persistent over time?
- Are there differences in the treatment effect across the quantiles of the gas consumption distribution?

3. The income elasticity of household energy demand;

   - Is there variation in the income elasticity of household energy demand across the energy expenditure distribution?
   - How do the quantile income elasticities of household energy demand compare to the benchmark constant mean elasticity?
   - What are the related policy implications?

4. Consumer switching in European energy markets;

   - What is the role of consumers' socio-demographic characteristics, together with their attitudes to the main features of the market, on the propensity to switch product/service or supplier?
   - How do the factors associated with consumer switching in energy markets compare to the factors associated with switching in markets more generally?
   - Are there differences in the factors associated with consumer switching across countries?

Thus, overall this thesis presents four discrete analyses that each separately examine issues relating to consumer engagement and heterogeneity in residential energy demand.

1.3 Data

The empirical essays presented in this thesis are based upon micro-econometric analyses. A significant advantage of using micro-data over aggregate data is that econometric models can allow for greater heterogeneity across individuals or households. Heckman (2001) claims that the fragility of aggregate data for inferring micro relationships reveals the "importance of using micro-data as the building block of an empirically based economic science". To this end, this thesis draws upon the best available experimental and observational micro-data to identify empirical evidence for the research objectives outlined above.

For the purpose of Chapter 2 and Chapter 3, experimental micro-data from Ireland's Smart Metering Gas Consumer Behavioural Trial (CER, 2011) is utilised. The trial was employed to establish the potential for smart metering, when combined with DSM stimuli, to promote behavioural change in the gas consumption of households. It is considered to be among the largest and most statistically robust smart metering behavioural trials of its kind to be conducted internationally (SEAI, 2012b), and it provides a rich panel of household gas consumption data together with a range of variables on the trial's participants, including their socio-economic, household level and dwelling characteristics. In addition, for the empirical analyses in Chapter 2 and Chapter 3, a dataset of daily weather variables from Met Éireann's Dublin Airport weather station was created. The weather data includes a variable on heating degree days, amongst other important meteorological variables.

Observational micro-data collected from five rounds of the Irish Household Budget Survey (HBS) and spanning a period of 23 years from 1987 to 2010 is used in Chapter 4. The HBS is a highly detailed survey of household income and expenditure, including spending on energy, for a representative random sample of all private households in Ireland. Its main purpose is to update the weighting basis of the Consumer Price Index (CPI) for Ireland. Additionally, the data contains useful micro-data on respondents' socio-economic and household characteristics.

The empirical analysis in Chapter 5 is based on observational micro-data from four independent cross-sections of the European Commission's Consumer Market Monitoring Survey (CMMS). The CMMS tracks the functioning of consumer markets across the EU to provide data for the Consumer Markets Scoreboard. The Scoreboard is used as an overall indicator for how well individual markets are functioning in EU Member States. The CMMS comprises a wealth of data on consumers' experiences in each market type across the key components of: comparability; trust; the extent to which the market lives up to expectation; complaints; and, consumer switching. Moreover, the CMMS has the additional advantages of being a pan European survey and containing micro-data on each consumer's socio-demographic characteristics.

Full details of each of these separate datasets are presented in the relevant chapters.

1.4 Overview of Thesis

Over the past twenty years there has been a remarkable growth in residential natural gas consumption in Ireland and, as a result, consumers can benefit from an understanding of the factors affecting their household gas demand to become better empowered to engage in the management of their consumption. Chapter 2 of this thesis examines in detail the determinants of residential gas demand in Ireland using a micro-econometric analysis of the daily gas consumption panel data from Ireland's Smart Metering Gas Consumer Behavioural Trial. It also investigates the effectiveness of the DSM stimuli, tested during the trial, in engaging households to conserve natural gas. The analysis employs a random effects regression model based on a sample of 1,181 households over 539 days. The results provide evidence that weather, together with the structural characteristics of the dwellings and the socio-economic characteristics of the households, are significant factors in explaining residential gas demand. More specifically, weather is found to be the most influential factor on household's daily gas consumption. Finally, through the implementation of a difference-in-differences estimation, the DSM stimuli employed in the trial are shown to reduce daily household gas use on average. A paper based on this research was published in *Energy Economics* in 2015.

While Chapter 2 demonstrates the effectiveness of smart metering enabled DSM for engaging households to reduce gas use, it is important for suppliers and policymakers to understand how the average effect varies across different groups of households in order to be able to offer a more targeted programme, engaging households in their energy transition. Chapter 3 explores the heterogeneous treatment effects of the DSM programme on residential gas consumption across different groups of households categorised by their socio-economic, household level and dwelling characteristics. This chapter also investigates the impact of the stimuli over time and across the distribution of daily household natural gas consumption. The results show that demand stimuli have very different effects across the socio-economic and dwelling characteristics of the households with older and larger households and dwellings revealed to be much more responsive to the feedback. Additionally, the impacts are shown to be quite persistent over time and the results provide evidence that the feedback encourages habit formation amongst households. The DSM stimuli are also found to be least effective on low gas users compared to high gas users. A paper based on this research is under review at *Energy Economics*.

For the protection and engagement of vulnerable consumers in the energy market, income support measures are provided as a policy response in a number of jurisdictions.

To achieve an accurate assessment of the policy's impact on energy consumption, it is important to make use of the most applicable income elasticity to the policy. Within this context, Chapter 4 examines variation in the income elasticity of household energy demand across the energy expenditure distribution using expenditure data from the five most recent HBSs in Ireland: the 1987, 1994/1995, 1999/2000, 2004/2005 and 2009/2010 HBS. The analysis uses a two stage instrumental variable quantile regression approach and is based on each HBS cross-section, as well as the overall pooled observations. The estimated elasticities are compared across low and high energy consumption scenarios and to a benchmark elasticity estimated using two stage least squares. The results provide evidence that there is significant variation in the income elasticities across the energy expenditure distribution and that care must be taken when using the constant mean elasticity for policy purposes. More specifically, any examination of the future impact of a change in income support policy measures on energy consumption should recognise the substantial context-dependent variation in the income elasticity. A paper based on this research was published in *Applied Economics* in 2017.

Enabling competition is the main rationale for restructuring and liberalising energy markets and consumer engagement through switching plays a significant role in creating competitive retail markets. Chapter 5 examines the factors influencing consumer switching in European energy markets using a micro-econometric analysis of consumer switching behaviour data from four pooled cross-sections of the European Commission's Consumer Market Monitoring Survey. It investigates the role of consumers' socio-demographic characteristics, together with their attitudes to the market, on the propensity to switch product/service or supplier. The results provide evidence that consumer attitudes to the market are highly significant factors in explaining consumer switching behaviour in energy markets, and in switching markets more generally. However, while consumer socio-demographic characteristics are significant factors in other switching markets, they are not significant factors in energy markets. Moreover, consumer complaints are revealed to matter most for consumer switching, while switching in energy markets is also found to be strongly associated with a higher propensity to switch in non-energy markets. Results also show that there is strong evidence of heterogeneity in the effects on switching across EU Member States. A working paper based on this research has been prepared.

Chapter 6 concludes this thesis and provides an overview of the main findings and policy implications that emerged from the four empirical essays. The final chapter also outlines the limitations of the research and potential avenues for future research.

1.5 Thesis Outputs

Journal Articles

Harold, J., S. Lyons, and J. Cullinan (2015). The determinants of residential gas demand in Ireland. *Energy Economics 51*, 475-483. doi: `https://doi.org/10.1016/j.eneco.2015.08.015`

Harold, J., J. Cullinan, and S. Lyons (2017). The income elasticity of household energy demand: a quantile regression analysis. *Applied Economics 49*(54), 5570-5578. doi: `http://dx.doi.org/10.1080/00036846.2017.1313952`

Journal Article Under Review

Harold, J., S. Lyons, and J. Cullinan (2017). Heterogeneity and habit formation in the effect of demand side management stimuli on residential gas demand. *Energy Economics*. Under Review.

Working Paper

Harold, J., J. Cullinan, and S. Lyons (2017). Consumer switching in European energy markets. Working Paper.

Conference and Seminar Presentations

Harold, J., S. Lyons, and J. Cullinan. The determinants of residential gas demand in Ireland

Presented at:

- The Electricity Research Centre Seminar, January 2014, University College Dublin, Dublin, Ireland
- The Brown Bag Seminar, March 2014, Discipline of Economics, National University of Ireland Galway, Galway, Ireland
- The Irish Economic Association 28th Annual Conference, May 2014, University of Limerick, Limerick, Ireland

Harold, J., J. Cullinan, and S. Lyons. The income elasticity of household energy demand: a quantile regression analysis

Presented at:

- The Irish Society of New Economists 11th Annual Conference, September 2014, National University of Ireland Galway, Galway, Ireland
- The Brown Bag Seminar, November 2014, Discipline of Economics, National University of Ireland Galway, Galway, Ireland
- The Irish Economic Association 29th Annual Conference, May 2015, Institute of Banking, Dublin, Ireland

Harold, J., S. Lyons, and J. Cullinan. Heterogeneity and habit formation in the effect of demand side management stimuli on residential gas demand

Presented at:

- Agricultural and Resource Economics Department Egg-timer Presentation, April 2016, University of California Berkeley, California, USA
- Young Energy Economists and Engineers Seminar, November 2016, International Centre for Mathematical Sciences, Edinburgh, Scotland
- The Irish Economic Association 31st Annual Conference, May 2017, Institute of Banking, Dublin, Ireland
- European Association of Environmental and Resource Economists 23rd Annual Conference, June 2017, Megaron Athens International Conference Centre, Athens, Greece

Conference Posters

Harold, J., S. Lyons, and J. Cullinan. The determinants of residential gas demand in Ireland

Presented at:

- The Engineers Ireland Energy Night, February 2015, National University of Ireland Galway, Galway, Ireland

Harold, J., J. Cullinan, and S. Lyons. Reducing energy use through behavioural change: the effect of demand side stimuli on residential gas demand

Presented at:

- The Whitaker Institute Research Day, April 2017, National University of Ireland Galway, Galway, Ireland

Chapter 2

The Determinants of Residential Gas Demand in Ireland[1]

2.1 Introduction

A better understanding of residential demand for natural gas can be of assistance to suppliers, policymakers and ultimately consumers. Suppliers need accurate forecasting models of residential gas demand to support efficient purchasing of gas supplies and to plan future investment in the face of changing demographics, fuel prices, macroeconomic conditions and energy policy measures. Such models exist, but they tend to be based on the analysis of annual micro-data and there is scope to improve these models using micro-data linking detailed household and socio-economic characteristics to daily gas use. Policymakers also have an interest in domestic fuel demand, because it contributes a significant proportion to national energy use and greenhouse gas emissions.

Residential natural gas consumption in Ireland has grown considerably in recent years. According to the Sustainable Energy Authority of Ireland (SEAI), natural gas as a share of total residential energy consumption increased from 5.2% to 20.1% over the period 1990-2011 (SEAI, 2012a), while the penetration of natural gas fired central heating systems into Irish houses has grown from 4% in 1987 to 28% in 2005 (SEI, 2008). In 2011, the residential sector in Ireland used 569 kilo tonnes of oil equivalent (ktoe) of natural gas compared to just 117 ktoe in 1990 (SEAI, 2012a). The remarkable growth in residential natural gas consumption in Ireland has been attributed to a number of factors including the large increase in the Irish housing stock since 1990, expansion of the gas network and a preference for natural gas on the part of residential users. The residential

[1]The research presented in this chapter is published as Harold et al. (2015).

sector in Ireland emitted 1,359 kilo tonnes of CO_2 from natural gas consumption alone in 2011, a 13% share of the overall energy-related household CO_2 emissions for that year (SEAI, 2012a). Residential heating, apart from that contributed by electricity, also falls outside the boundaries of Europe's Emission Trading Scheme (ETS), in a segment where there is not (yet) a common, consistent set of economic measures to provide incentives for carbon abatement across Europe. Overlapping policies towards carbon abatement, energy efficiency and encouragement of renewable fuels complicate the policy space in this area.

To curb carbon emissions and increase energy efficiency, policymakers employ a range of measures intended to change aspects of consumer behaviour. This may include encouragement of fuel switching, increased energy efficiency or changes in other aspects of behaviour that lead to lower fuel use. Better understanding the determinants of gas demand should help with the development of more effective and efficient policy measures. Information about consumer behaviour is particularly important when designing demand side management (DSM) programmes. These are used in some jurisdictions to bring about behavioural change among consumers, aiming to reduce fuel consumption by either improving the information available to households on potential energy efficiency opportunities or by giving them a financial incentive to decrease their overall household gas use. It is important for energy policy to investigate the usefulness of such programmes in reducing household gas consumption and to incorporate the factors affecting daily gas demand into programme design, in order to maximise the potential impact on consumer behaviour.

In this chapter, the determinants of residential gas demand in Ireland are examined using a micro-econometric analysis of the gas consumption panel data from Ireland's Smart Metering Gas Consumer Behavioural Trial (CER, 2011). It is unusual for studies of gas demand to have access to such high frequency usage data combined with socio-economic micro-data. With the majority of residential gas consumption in Ireland used for space and water heating, gas demand is expected to be determined to a large extent by the energy efficiency of gas using appliances and dwellings, as well as the socio-economic characteristics of the household. It is also anticipated that weather will have a significant role in determining household gas demand. For example, gas consumption reportedly experienced an unusual increase in 2010 as a result of two exceptionally cold spells at the beginning and end of the year.

This chapter aims to provide evidence that the energy efficiency of the dwellings, together with the socio-economic characteristics of the households and the weather are indeed important factors in determining daily residential gas demand and should, for

that reason, be taken into account in gas demand forecasting. In addition, this chapter explores the impact of socio-economic factors on household consumption of gas and investigates the DSM stimuli tested during the smart metering trial, demonstrating their effectiveness in reducing household gas consumption through the implementation of a difference-in-differences estimation of the gas savings.

The chapter proceeds as follows: the related literature is reviewed in Section 2.2, the data and variables used are described in Section 2.3, details of the models used for estimation are specified in Section 2.4, results are presented in Section 2.5, and Section 2.6 provides a conclusion.

2.2 Literature

Much of the literature on residential gas demand focuses on estimating elasticities of demand using time-series data. For example, Bernstein and Madlener (2011) analyse residential natural gas demand in 12 OECD countries including Ireland from 1980 to 2008 and find that the long run price elasticity for Ireland is -1.62, while the long run income elasticity is 1.72. On average across all the countries, the long run elasticities with regard to price and income are found to be -0.51 and 0.94 respectively, with demand in Ireland being the most elastic of the 12 countries in this analysis. Asche et al. (2008) report that the own-price elasticity of natural gas is very inelastic in the short run, though it does demonstrate greater responsiveness in the longer run. This is most likely due to the limited substitution possibilities between different fuels in the short run. In considering the ownership of energy-using durables and the demand by individual households in the UK for gas and electricity, Baker and Blundell (1991) use data pooled from the family expenditure survey (FES) over the period 1972 to 1988. They also report demand for natural gas to be generally price inelastic.

While there is a limited body of research which specifically examines the determinants of residential gas demand, some important related research has been conducted in the area. For example, Brounen et al. (2012) examine the extent to which gas and electricity use in the Netherlands is determined by household and individual characteristics. They found that residential gas consumption was driven largely by dwelling characteristics, with older and bigger homes found to consume more gas. They also note that insulation had a significant effect on gas consumption by households and that "residents living in a well-maintained and insulated home consume about 12% less natural gas compared to the same home with a lower level of maintenance and insulation" (Brounen et al., 2012). Interestingly, it was found that each additional person

in a household decreases the per capita gas consumption by roughly 26%. According to the authors, "this reaffirms the well documented economies of scale in residential energy consumption" (Brounen et al., 2012). On the other hand, single-parent and elderly households were found to use more natural gas per capita. This is consistent with findings from a study of demand for space and water heating by older households in the United States. In particular, Liao and Chang (2002) reported that most elderly households spend a significant amount of their income on space heating energy and as the household head becomes older more heating energy is required.

In another study, Leth-Peterson (2002) conducted a micro-econometric analysis of household demand for natural gas for a cross-section of 2,885 Danish households. The year in which the house was built as well as the house type were found to be important determinants of gas demand. The consumption of natural gas in non-detached houses was found to be 4% lower than in detached houses. In an analysis of residential heating consumption in the Netherlands, Guerra-Santin and Itard (2010) found that the frequency of use of the heating system was a much stronger determinant than temperature settings in explaining energy consumption by households. Interestingly, they found that "households with a programmable thermostat were more likely to keep the radiators turned on for more hours than households with a manual thermostat or manual valves on radiators." Karjalainen (2007) found significant gender differences in thermal comfort, with females preferring a higher room temperature than males. However, males tend to use thermostats more often than females in their sample.

In contrast to residential natural gas demand, there is a larger literature on energy demand for residential space and water heating more generally. For example, Rehdanz (2007) studies the determinants of household expenditure on space heating and hot water supply in Germany in an attempt to establish if different types of households respond differently to changes in energy prices. The analysis covers more than 12,000 households for the years 1998 and 2003. The author points out that energy price increases lead to higher expenditures for households in rented accommodation compared to households in owner occupied accommodation with the difference becoming smaller over time. This suggests that home owners are more likely to have invested in energy efficient heating and hot water systems and, furthermore, that landlords have very little incentive to improve the energy efficiency of rented accommodation as their tenants pay the energy bills. In a replica study for Great Britain, Meier and Rehdanz (2010) utilise panel data over 15 years from 1991-2005 on over 5,000 households and discover the opposite result. The study finds that heating expenditure for home owners tend to be higher than for renters. Heating expenditures are lowest for flats compared with

households living in other house types and as the majority of rented accommodations in Britain are flats, this explains the contradicting result.

In examining residential energy consumption for space heating in Norwegian households, Nesbakken (2001) confirms that house type, dwelling size and temperature (degree days) are important in explaining energy demand in households. Furthermore, Druckman and Jackson (2008) explore patterns of UK household energy use at high levels of socio-economic and geographical disaggregation. Their results show that rural/urban location is also an important factor in household energy consumption. In a study examining the effect of a major energy efficiency refurbishment programme on domestic space heating fuel consumption in English dwellings, Hong et al. (2006), using data collected from 1,372 households participating in the 'Warm Front' energy efficiency scheme, found that attic and cavity wall insulation appeared to reduce space heating fuel consumption by 10-17%.

Another strand of literature in this area investigates the impact of weather on demand for energy. For example, Conniffe (1996) developed a model to help explain how daily demand for fuel by the domestic and commercial sectors in Ireland varies from day to day in response to different factors including meteorological variables. The author estimates the model for natural gas and establishes that temperature measured as degree days is non-linear in the demand for gas. He also found that wind speed and sunshine hours have substantial effects on gas demand, while the significance of rainfall is much less pronounced in the model. Tol et al. (2012) also find that energy use is non-linear in temperature and that it declines with rising temperatures due to the decreased demand for heating.

In the Irish context, Rogan et al. (2012) performed a decomposition analysis of residential gas consumption in Ireland from 1990 to 2008 and report that the change in the number of customers had the greatest effect on gas consumption. In the period of the examination, Bord Gáis Éireann was the only natural gas retailer to the residential sector in Ireland. They had 139,000 customers in 1990 and by 2008 their customer base had grown by 342% to 616,000 customers. The CER (2011) Gas Customer Behaviour Trial Findings Report found that the smart metering trial had a positive impact on the awareness of residential gas usage in Ireland, with 74% of households reporting that they became more aware of their gas consumption. It also reported that the deployment of the demand side stimuli reduced overall gas consumption by about 2.9%.

2.3 Data

For the purpose of this chapter, micro-data which was collected as part of Ireland's Smart Metering Gas Consumer Behavioural Trial (CER, 2011) is used. The trial was run from 1st December 2009 to 30th May 2011 and had two distinct periods, the benchmark period and the treatment period. During the benchmark period (1st December 2009 to 31st May 2010), all participants were charged their normal tariff and received bi-monthly billing. Data collected during this period was for the purpose of establishing the benchmark level of use by households. During the treatment period (1st June 2010 to 30th May 2011), participants were divided into treatment and control groups. The treatment groups were placed on different DSM stimuli while the control group remained on their normal tariff and had no changes to their bill. The DSM stimuli tested in the trial included providing the household with additional information on their gas usage; a more frequent bill (monthly), the provision of an In-House Display (IHD) unit; and the introduction of a variable tariff[2]. Participant selection and recruitment was limited to customers of Bord Gáis Energy, which represented close to 100% of the residential gas market. The recruitment was phased to ensure the sample was representative of the national gas consumer population and it was conducted on a voluntary basis using a tear off slip at the bottom of an invitation letter. Data was collected on a half hourly basis from 1,892 household meters over the complete course of the trial. At the end of the complete period, 1,576 household meters remained in the trial after attrition. Changes of tenancy and changes of supplier were cited as the main reasons behind the attrition.

While 103 of the remaining household meters have complete gas data, 1,473 had at least one missing half hour entry in the trial period. Bord Gáis Networks carried out work during the trial to establish why meters had missing data, and it is suspected in the majority of cases that the reason was of a technological nature, such as transmission failure. The meters with more than 8 weeks missing data were removed together with the data for 6 particular days, where more than 15% of the meters had missing values. Furthermore, the data for the 27th March 2011 (daylight savings time) was deleted as there were two additional half hour periods recorded on that day for which there was no obvious way to attribute gas use. The remaining meters with missing data had the missing values imputed by statisticians at the Commission for Energy Regulation (CER) using a method of multiple imputation. This involved estimating a mean value by calculating an average of six values, the two values immediately preceding and after

[2]More details of the 'treatments' are presented in Chapter 3.

the missing value; the values during the same half hourly period one week before and after; and the values for the same period two weeks before and after. The uncertainty associated with the imputed value is measured by the standard deviation of the six values. The multiple imputation process then replicates the data series for the missing meters and completes the data with values obtained by reference to the distributions given by the mean and standard deviation calculated. The imputation was carried out for 1,390 of the households with missing gas data. Consequently, complete gas data is available for 1,493 households with the imputed values accounting for just 0.5% of all values (CER, 2011).

Additionally, pre- and post-trial surveys were conducted among the participating households using Computer Assisted Telephone Interviewing (CATI). These surveys explored the structural and socio-economic characteristics of the household as well as the attitudes of the respondents with regard to energy saving activities. The surveys also investigated the presence and use of gas appliances in the home. A further 312 households were dropped from the analysis for failure to answer some key socio-economic and housing characteristic questions, such as the number of bedrooms or the year the house was built.[3] Thus. the data used in the analysis in this chapter includes the daily household gas consumption (kWh) for 1,181 households over the trial period of 539 days (546 days less the 7 days dropped), the socio-economic and housing characteristic variables from the pre-trial survey for each of these households, along with daily weather data provided by Met Éireann's Dublin Airport weather station.

Figure 2.1 illustrates the frequency of daily gas consumption (kWh), the dependent variable, in the sample. The distribution of daily gas consumption is skewed to the right with the high frequency of low consumption days reflective of the high seasonality of gas consumption. The mean daily gas consumption in this sample is 47.8kWh (see Table 2.1). The minimum daily gas consumption is as expected at 0kWh, though the maximum daily consumption gives some cause for concern at 530.49kWh. There are only 20 observations with daily gas consumption above 400kWh with 19 of these falling in late December and early January, a particularly cold period in the calendar. 15 of these observations are for households that own two or more gas fires along with their gas fired central heating system. Therefore, while the maximum of 530.49kWh is very high, it is possible.[4]

[3]There is no evidence to suggest that this would introduce a bias from an examination of the profile information available about these households.

[4]The analysis was also performed excluding the 20 observations with daily gas consumption above 400kWh and the estimated coefficients were robust to the omission of these outliers (see Appendix A, Table A.1).

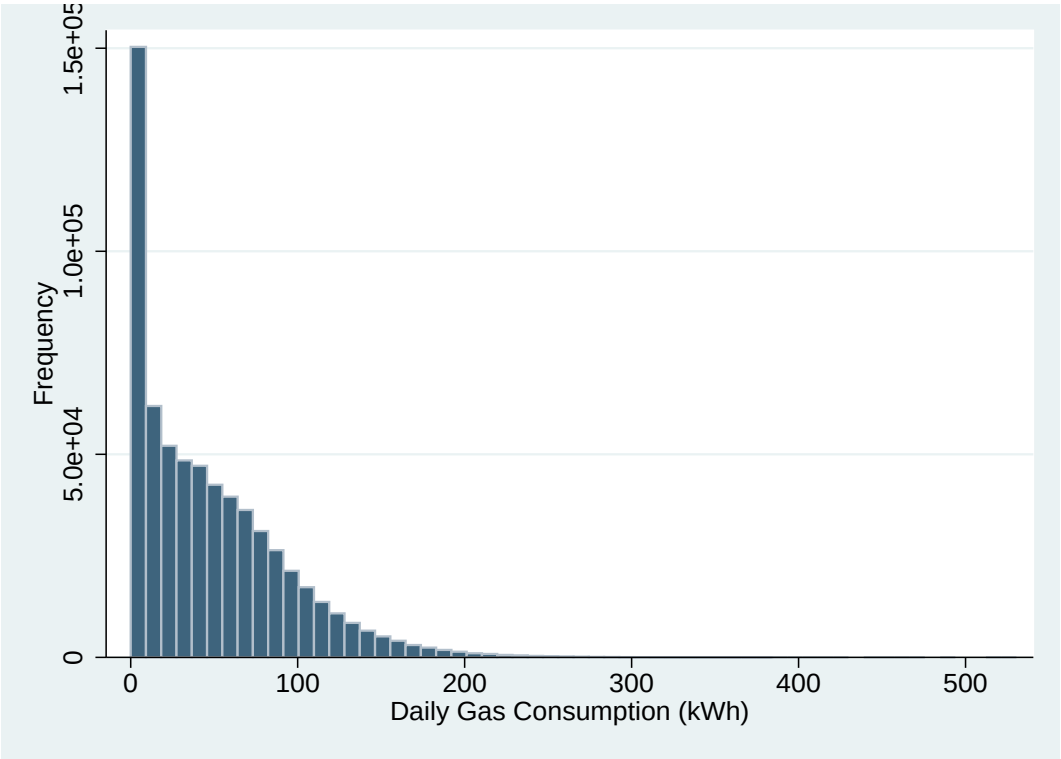

Figure 2.1: Frequency of daily gas consumption (kWh).

Table 2.1: Descriptive statistics for daily gas consumption.

	Mean	**St. Dev.**	**Min**	**Max**	**T**	**N**
Daily Gas Usage (kWh)	47.8	45.2	0	530.49	539	1181
Daily Duration of Gas Usage (1/2 hour)	16.1	14.1	0	48	539	1181

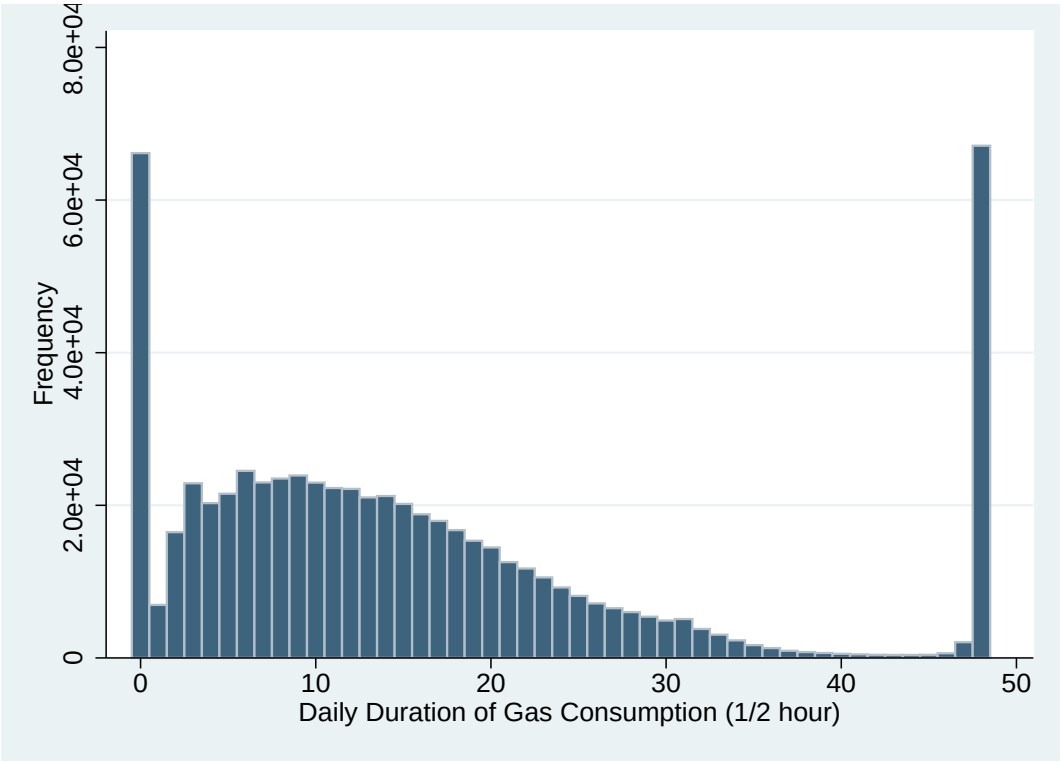

Figure 2.2: Frequency of daily duration of gas consumption ($\frac{1}{2}$hour).

The pattern of household gas consumption is represented in Figure 2.2. The histogram shows the frequency of the number of half hours in a day the gas is switched on across all households for the entire period. The high frequency of low gas use once again reflects the high seasonality in gas usage. The distribution of the usage of daily gas consumption becomes larger from one half hour to about 6 half hours with the distribution skewed to the right thereafter with a single bar spike at 48 half hours. It is not remarkable for a household to be much more likely to have gas on for just 6 half hours in a day in contrast to having it on for 35 half hours in a day. On the contrary, the high frequency of all day gas use is interesting and requires further analysis beyond the scope of this analysis. There may be some unobserved controls that are not in the data which would help explain such a high frequency. For example, it could be explained by a pilot light installed on some gas fires and gas central heating systems, which burns continuously and therefore results in gas usage being recorded for all half hour periods in a day.

In terms of explanatory variables, the data on the socio-economic and building characteristics of the households was collected as part of a pre-trial survey between April and May 2010 and just before the test period commenced. The price of gas is not included in this analysis because there is very little price variation across the time period

analysed. All participants are faced with the same set of prices with the exception of those placed on a variable tariff as a result of the demand side stimuli introduced in the trial. It is also important to note that given the high rate of non-response to the income question in Ireland's Smart Metering Gas Consumer Behavioural Trial (CER, 2011), income could not be controlled for in this analysis. However, other socio-economic factors strongly correlated with income, such as education and employment status are included. These variables should help to mitigate some of the effects of any suspected omitted variable bias.

The summary statistics of the selected categorical and dummy variables important to this analysis are described in Table 2.2. At first glance, the 18-25 age group appears to be under represented in the sample at 0.4%; however, given that the chief economic supporter's (CES's) are gas bill payers it is expected that few respondents would fall into the 18-25 age category and therefore the fact that 0.4% is not representative of the national population of 18-25 year olds is not a problem for this analysis. For education, 76% of the sample has at the very least completed their Leaving Certificate examinations. The number of bedrooms is used as a proxy for house size, with 1-2 bedroom households accounting for just 9% of the sample, reflecting the fact that these smaller households are less likely to have gas central heating installed. This is backed up by the fact that apartments only account for 2% of households in the data. Houses built after 1980, when significant building thermal insulation requirements were introduced (1979), represent 51% of the sample. The profile of participants and their dwellings in this analysis is in line with Ireland's Smart Metering Gas Consumer Behavioural Trial (CER, 2011), which is deemed representative of the entire population of natural gas consumers.

In the pre-trial survey, details about the dwelling characteristics were also collected and respondents were asked to give the approximate proportion of windows in their house that are double glazed. For the purpose of this study, any household that answered any proportion apart from none was deemed to have double-glazing. Consequently, it is observed that 94% of households have some proportion of double-glazing. Households with attic insulation account for 91% of the sample. 2% of households were unaware whether or not they had attic insulation; this is not a significant share and does not highlight an unawareness issue. Conversely, 16% of households didn't know if they had external wall insulation, 11% do not have a lagging jacket on their hot water cylinder and 9% of households in the sample state that they have never had their boiler serviced. This could potentially signal an unawareness of certain energy efficiency measures. Nevertheless, there is not enough evidence here to draw conclusions in relation

Table 2.2: Proportion of households in the different variable categories.

		%			%
Female		47.0	**Number of Bedrooms**		
			1-2 Bedrooms		9.0
Age			3 Bedroom	*Ref*	50.6
18-25 years		0.4	4 Bedrooms		34.5
26-35 years		14.6	5+ Bedrooms		5.9
36-45 years	*Ref*	27.9			
46-55 years		23.9	**Period House Built**		
56-65 years		16.0	Pre 1900		3.6
65+ years		16.3	1901-1940		9.6
Refused		0.9	1941-1960		11.5
			1961-1980		24.0
Education			1981-2000	*Ref*	32.0
None		1.4	2001-2008		19.3
Primary		6.9			
Junior Cert		11.9	**Dwelling Characteristics:**		
Leaving Cert		22.5	**Double Glazing**		94.3
Third Level	*Ref*	53.3			
Refused		4.0	**Attic Insulation**		
			<5 years		27.3
Employment Status			>5 years	*Ref*	63.7
Employee	*Ref*	60.0	None		6.7
Self-employed (employees)		5.3	Don't Know		2.3
Self-employed (no employees)		6.4			
Unemployed		6.6	**External Wall Insulation**		
Retired		20.7	Yes	*Ref*	49.4
Care Giver		1.0	No		34.9
			Don't Know		15.7
Number of Household Members					
1 Person		16.1	**Boiler Service**		
2-3 People	*Ref*	50.6	Never		9.2
4-5 People		29.3	Every 2-3 years		36.5
6+ People		4.0	Every year	*Ref*	54.3
Tenure (Rented)		5.8	**Lagging Jacket**		89.1
House Type			**Booster Button**		40.1
Apartment		2.2			
Semi-Detached	*Ref*	56.2	**Fire Effects Gas Fire**		47.3
Detached		17.7			
Terraced		20.2			
Bungalow		3.7			

Note: *Ref* is the omitted reference category.

to any efficiency awareness issue. Almost half of all households have at least one fire effects gas fire and 40% have a booster button on their heating system which allows the household to switch on the space or water heating for an additional hour.

Because weather plays such an important role in energy demand generally, a more detailed discussion of the weather variables is relevant. The weather data that is used is from Met Éireann's Dublin Airport weather station and comprises variables on heating degree days, sunshine hours, mean cloud cover, daily rainfall and wind speed. Information on the location of households is not available in the data, thus, the weather data is taken for Dublin as it is the area with the highest population density in Ireland and it also has the highest concentration of household gas meters in the whole country. The descriptive statistics for the weather variables are described in Table 2.3.

Table 2.3: Descriptive statistics for the weather variables.

	Mean	**Std. Dev**	**Min**	**Max**	**T**
Heating Degree Days	8.07	5.14	0	23.3	539
Sunshine Hours (hours)	4.54	3.8	0	15.8	539
Cloud Cover (oktas)	5.48	1.56	0.54	8	539
Rainfall (mm)	1.67	3.25	0	28.4	539
Wind Speed (knots)	9.84	4.11	2.33	28.8	539

The impact of temperature on the heating requirements of a house is provided for by heating degree days. Heating degree days is a measurement derived from outside air temperature; it is defined relative to a base temperature, the outside temperature above which a building needs no heating. The base temperature here is 15.5^{o}C in line with other studies. If the average daily temperature is one degree below the base of 15.5^{o}C, then this is referred to as one heating degree day. The larger the number of heating degree days, the colder it is and so the bigger the requirement on the heating system. In the sample, the average heating degree days based on the arithmetic mean is slightly over 8 heating degree days. This reports that on average the daily temperature is 8 degrees below the base of 15.5^{o}C and thus the average daily temperature in the sample is about 7.5^{o}C across the 539 days. Temperatures over and above the base are not deemed to have an effect on the heating requirement, with the outside base temperature of 15.5^{o}C equating to the satisfactory temperature for human thermal comfort indoors. The minimum heating degree days is 0 when the temperature is greater than or equal

to 15.5^{o}C and the maximum in the data is 23 heating degree days, where a temperature of -7.5^{o}C was recorded at Dublin Airport during an unusually cold spell over Christmas 2010.

Sunshine hours are a measure of the duration of sunshine in a day. The average daily duration of sunshine across the period is a little over 4.5 hours. According to Met Éireann, Ireland normally gets between 1,400 and 1,700 hours of sunshine each year and the daily average of 4.5 hours here corresponds with this information. On a cloud covered day the minimum sunshine hours of 0 is documented, while on the summer solstice (21st June 2010) a maximum of 15.8 sunshine hours is observed. Mean cloud cover measures the average daily amount of cloud cover. Oktas are the unit of measurement for cloud cover. Oktas are estimated with respect to how many eighths of the sky are covered by cloud. They range in value from 0 to 8, with 0 representing a completely clear sky and 8 representing a completely overcast sky. The average daily cloud cover across the 539 days is almost 5.5 oktas. Irish skies are predominantly cloudy due to Ireland's position in the northwest of Europe close to the path of the Atlantic low pressure systems. As expected, sunshine hours and mean cloud cover are highly negatively correlated.

Daily rainfall is measured in millimetres (mm). The average daily rainfall is recorded at 1.67mm over the sample period in line with Met Éireann's reported average daily rainfall for Ireland of between 1 and 2mm. The maximum daily rainfall of 28.4mm was recorded in December 2009 when Ireland suffered from a period of extensive flooding. The daily mean wind speed is measured in knots. A knot is a unit of speed equal to one nautical mile per hour, equivalent to 1.852km per hour. The average daily wind speed in the period for the analysis is over 9.8 knots (18.15km per hour) with the maximum of over 28 knots recorded in early February 2011.

In the analysis, dummy variables are added for weekends and bank holidays, together with dummies for each of the four seasons. In addition, for a difference-in-differences analysis of the demand side stimuli in the trial, dummies are also introduced for the treatment period, the treatment group and the interaction between treatment period and group. This is discussed in more detail in the next section.

2.4 Methodology

The main model for estimation assumes that the demand for gas depends on a range of variables, such that:

$$G_{it} = \alpha_i + \beta X_i + \gamma Y_i + \delta W_t + \tau D_{it} + \pi Z_i + \epsilon_{it} \tag{2.1}$$

where the dependent variable G_{it} denotes the daily natural gas demand of household i at time t, and X_i is a vector of the socio-economic characteristics of the CES in the household, which includes gender, age, education, and employment status. Y_i is a matrix of household level characteristics, which include the number of household members, a dummy variable for whether the house is rented or owned, the house type, the number of bedrooms and the period in which the house was built. W_t represents the weather variables, D_{it} are the time and season dummies, together with the treatment period and group dummies. Z_i is a matrix of dwelling characteristics, which range from features that enhance the energy efficiency of the household such as attic insulation and double glazed windows, to devices that contribute to a household's greater energy use such as a booster button and a fire effects gas fire. The error term is denoted by ϵ_{it}. There may also be unobserved household specific factors that impact on gas consumption, for example, individual levels of thermal comfort. The unobserved household-level heterogeneity that is constant over time is taken into account by α_i and the model is estimated using a random effects estimator with cluster robust standard errors clustered at the household level.

Conniffe (1996) identifies weather as the main determinant of natural gas consumption. Hence, the weather variables are an essential inclusion in the gas demand model. Heating degree days, which measure the temperature impact on the building's heating requirement, is expected to be a highly significant factor in the household's daily gas usage. The coefficient is predicted to be positive as a high number of heating degree days indicates a colder day and an increased requirement for gas energy use to preserve a satisfactory household thermal comfort. Sunshine hours and cloud cover are introduced in the model because of possible smaller impacts on a household's gas demand when compared with heating degree days. It is anticipated that the signs on the coefficients for sunshine hours and cloud cover will be positive and negative respectively, given the high negative correlation that exists between the two variables. An overcast day has no sunshine and is associated with cooler temperatures. In controlling for wind speed and rainfall, there is no a priori expectation. However, Conniffe (1996) finds that wind has quite a substantial effect on gas demand while rainfall is less significant.

Time dummies which account for the effects of weekends and bank holidays are added to control for the fact that a household's daily demand for gas would normally increase on these specific days due to the greater likelihood of household members being at home all day. Furthermore, dummies for the seasons, winter, spring, summer and autumn are included with summer as the reference season. This will assist in unravelling any additional impacts the seasons have on household gas demand over and above the usual weather effects.

In order to account for the treatment and control effects of the smart metering trial a difference-in-differences approach is used as outlined in Angrist and Pischke (2008). In this approach, a dummy for the treatment period that switches on for observations in the test period from 1st June 2010 to 30th May 2011 is included. In addition, a dummy for the treatment group is also necessary and it switches on for observations in the test group. The treatment group dummy should be insignificant as the households were randomly selected in the sample to take part in the different demand side stimuli. In order to measure the treatment effects on gas demand, an interaction term that marks observations from the treatment group in the treatment period is also included. If the demand side stimuli, such as the additional usage information on the gas bill or the installation of an IHD unit, were successful in reducing gas demand then the coefficient on the interaction term should be negative and significant.

Bertrand et al. (2004) argue that most dependent variables in difference-in-differences estimation are highly positively serially correlated, and as a result, the standard errors are inconsistent. It is reasonable to accept that the dependent variable used here, daily gas usage, is highly positively serially correlated. This is addressed by allowing for clustering of standard errors at household level, as suggested by Angrist and Pischke (2008).

2.5 Results

Table 2.4 presents the results of the random effects regressions examining the factors influencing the daily gas consumption of households in the sample. The table presents the estimated coefficients from three models, and the first model includes the CES's socio-economic and household level characteristics. The second model includes the independent variables from the first model together with the weather variables, time dummies and treatment controls and finally the third model also includes the energy efficiency dwelling characteristics. An examination of the estimated coefficients across all three models tests the robustness of the findings. The reference category for each of

the categorical explanatory variables act as a baseline against which the household's different characteristics can be compared. The final model has an R-squared of 0.585 and accordingly explains almost 60% of the variation in daily residential gas consumption with the estimated coefficients confirming robustness across the models. The standard errors are reported in Appendix A, Table A.2.

Table 2.4: Estimated coefficients from the random effects models of daily gas usage.

VARIABLES	(1) Daily Gas Usage	(2) Daily Gas Usage	(3) Daily Gas Usage
Female	-0.0788	-0.0506	0.0215
Age			
18-25 years	-6.846	-7.146	-5.482
26-35 years	-5.075***	-5.081***	-4.945***
36-45 years	*Ref*	*Ref*	*Ref*
46-55 years	2.502*	2.531*	2.2
56-65 years	2.412	2.469	1.9
65+ years	5.833**	5.841**	5.197*
Refused	9.377**	9.588**	7.608
Education			
None	-5.773	-5.744	-5.015
Primary	-4.347**	-4.354**	-4.947**
Junior Cert	-0.365	-0.384	-0.608
Leaving Cert	-1.069	-1.089	-1.351
Third Level	*Ref*	*Ref*	*Ref*
Refused	0.579	0.459	0.766
Employment Status			
Employee	*Ref*	*Ref*	*Ref*
Self-employed (employees)	8.108***	8.217***	8.731***
Self-employed (no employees)	3.824	3.912	4.357*
Unemployed	-0.186	-0.0932	-0.3
Retired	2.322	2.309	2.096
Care Giver	6.346	6.257	6.92
No. of Household Members			
1 Person	-7.465***	-7.528***	-7.608***
2-3 People	*Ref*	*Ref*	*Ref*
4-5 People	2.510**	2.516**	2.690**
6+ People	3.565	3.439	3.829
Tenure (Rented)	-7.585***	-7.678***	-7.013***

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Table 2.4 – continued from previous page

VARIABLES	(1) Daily Gas Usage	(2) Daily Gas Usage	(3) Daily Gas Usage
House Type			
Apartment	-6.910*	-6.975*	-5.762
Semi-Detached	*Ref*	*Ref*	*Ref*
Detached	4.001**	3.983**	4.230***
Terraced	-1.892	-1.865	-1.89
Bungalow	5.590**	5.553**	6.573***
Number of Bedrooms			
1-2 Bedrooms	-3.611*	-3.512*	-3.173*
3 Bedrooms	*Ref*	*Ref*	*Ref*
4 Bedrooms	10.55***	10.60***	10.27***
5+ Bedrooms	20.30***	20.37***	20.98***
Period House Built			
Pre 1900	13.52***	13.42***	12.62***
1901-1940	9.606***	9.532***	8.353***
1941-1960	5.856***	5.823***	4.308**
1961-1980	7.468***	7.424***	6.336***
1981-2000	*Ref*	*Ref*	*Ref*
2001-2008	-0.818	-0.779	0.26
Weather			
Heating Degree Days		4.699***	4.699***
Sunshine Hours		-1.039***	-1.039***
Cloud Cover		0.817***	0.817***
Rainfall		0.138***	0.138***
Wind Speed		0.947***	0.947***
Time			
Weekend Day		0.661***	0.661***
Public Holiday		3.041***	3.041***
Treatment Period		-1.344**	-1.344**
Treatment Group		-0.0798	-0.117
TreatmentGroup*Period		-1.537**	-1.537**
Winter		22.06***	22.06***
Spring		10.69***	10.69***
Autumn		3.394***	3.394***
Dwelling Characteristics			
Double Glazing			-0.104
Attic Insulation			
<5 years			-2.196*
>5 years			*Ref*

Continued on next page

Table 2.4 – continued from previous page

VARIABLES	(1) Daily Gas Usage	(2) Daily Gas Usage	(3) Daily Gas Usage
None			-4.319**
Don't Know			-1.129
External Wall Insulation			
Yes			*Ref*
No			4.537***
Don't Know			1.17
Boiler Service			
Never			-4.218**
Every 2-3 years			-2.266**
Every year			*Ref*
Lagging Jacket			-1.051
Booster Button			1.903*
Fire Effects Gas Fire			2.555**
Constant	38.19***	-18.11***	-18.09***
Observations	636,559	636,559	636,559
Number of ID	1,181	1,181	1,181
R^2	0.069	0.58	0.585
		***p<0.01, **p<0.05, *p<0.1	

In terms of the results, the gender of the CES has no significant effect on the daily gas consumption by households. This is in contrast to Karjalainen's (2007) finding that females prefer higher room temperatures to males. However, as the data collected for the smart metering trial is focused on households rather than individuals, no relevant inference can be made here about the gender differences in daily gas consumption. Households with the CES aged 26 to 35 years consume less gas daily than households with the CES in the age reference category 36 to 45 years. Households with the CES over 65 years old consume more gas relative to those in the 36 to 45 years age category in both the first and second model, though when the dwelling characteristics are incorporated in the third model the significance is less. This finding is in agreement with Liao and Chang's (2002) finding that as the household head becomes older more heating energy is required.

In terms of education, the prior expectation was that education may be a signal of an increased awareness of energy efficiency concerns and that higher education could possibly be associated with a decrease in gas consumption. However, contrary to this expectation, the opposite is found, with households with lower levels of CES educational attainment using less gas daily on average. However, this may be capturing an income effect, with higher education being correlated with higher income; highly educated households have the means to consume more gas than the lower educated households. In addition, households with a self-employed CES with employees consume significantly more gas in a day than households with an employed CES. Self employed people with employees tend to earn more than employees and as a result have more resources to consume gas. Thus, this significance may also be explained by an income effect or could be partly explained by their propensity to work from home, something that was not possible to identify in the data.

As expected, the number of household members has a highly significant effect on the daily gas consumed by households. Relative to the reference category of 2-3 household members, a single person household consumes considerably less gas daily and a household with 4-5 members consumes moderately more. The households with 6 plus members are too few in the sample to make any inference. The additional members in a household reveal a reduction to the per capita gas consumption of the household; this result gives further evidence to the "well documented economies of scale in residential energy demand" (Brounen et al., 2012).

The results also suggest that homeowners consume significantly more natural gas in a day than their renting counterparts. This result is consistent with Meier and Rehdanz (2010), who found that renters use less gas than owners, primarily because the highest proportion of renters are inclined to occupy flats or apartments which by their nature are much more energy efficient. However, the same cannot be said here. In the sample nearly 37% of renters live in semi-detached houses, compared to less than 9% in apartments. The significant result could instead be due, once again, to an underlying income effect. Over 38% of homeowners own their homes outright in the sample and as a result may have the disposable income to increase their daily gas consumption, whereas renters after rent is paid may have less disposable income to spend on natural gas.

Households living in detached houses and bungalows demand comparatively more gas daily than those in semi-detached houses. As discussed in Wyatt (2013), this may be due to both detached houses and bungalows having more external walls, resulting in an extra requirement for natural gas because of the additional heat loss. Semi-

detached houses on the other hand benefit from the additional insulation afforded them from not having all their walls exposed to the elements. Thus, Leth-Peterson's (2002) finding that house type is an important determinant of gas demand is confirmed by this analysis. The number of bedrooms provides additional information in this regard. Households living in four and five bedroom houses consume more gas than those in three bedroom houses, while alternatively, households in one and two bedroom houses consume a relatively smaller amount of gas when compared to households in three bedroom houses. As the number of bedrooms increases, the household daily gas consumption increases notably and therefore, in line with expectations, house size is a highly significant determinant of daily residential gas demand.

Households in houses built pre 1981 consume considerably more natural gas than those in houses built in the period from 1981-2000. Interestingly, the thermal insulation requirements for buildings in Ireland were introduced in 1979. It is possible that the standards of energy efficiency in the new housing stock improved substantially from 1979 onwards and this effect is picked up in the analysis as a reduction in daily household gas demand post 1980. This result reaffirms Brounen et al.'s (2012) finding that residential gas consumption is driven largely by the period in which the house was built. It is noteworthy that the older the house relative to the 1981-2000 period, the greater the household daily gas consumption, with houses built pre 1900 exhibiting the most gas use.

All the weather variables are found to be highly significant determinants of residential natural gas consumption in Ireland, echoing findings from Conniffe (1996). Indeed, the second model has an R-squared of 0.58, up from 0.07 in model (1), which suggests that the weather variables controlled for here result in a large improvement in the fit of the model. Of the weather variables, heating degree days have the largest positive association with household daily gas consumption. The results reveal that large heating degree days indicate colder temperatures and a considerable increase in daily residential gas demand. It would be interesting to model heating degree days following the approach used in Conniffe (1996) and establish the effect of heating degree days on gas consumption when taking into account the long run degree days and the nonlinearity of temperature; however, this is beyond the scope of this study.

The results suggest that sunshine hours have a negative effect on residential gas demand. The more sunshine observed in a day, the less gas consumed by households. The sunshine effect may be a supplementary effect to heating degree days, where a household on a cold day with lots of sunshine would consume less gas than a household on a cold day with no sunshine, as a direct result of the sunshine having a strong

association with warm temperatures. In contrast, cloud cover has the opposite effect with the model producing a positive coefficient. On a cloudy day households consume more gas. These results reiterate the strong negative correlation between both sunshine hours and cloud cover.

While Conniffe (1996) finds little effect of rainfall on gas demand, rainfall proves to be highly significant and increases the demand for natural gas by households in this analysis. The reason for this impact of rainfall on daily residential gas demand is not particularly clear, however; it may be that rain gives individuals the feeling of cold or quite possibly rain gives rise to an increased requirement to dry clothes indoors. Like the Conniffe (1996) model, wind is an important determinant for residential gas demand with increased wind speeds culminating in greater daily gas consumption by households.

In terms of time of use, households consume more gas at the weekends and on public holidays. This is because houses are much more likely to be occupied on these days when adults are off work and children are off school. The augmented requirement for space and water heating leads to an increase in household gas consumption on these particular days. In winter, spring and autumn households consume relatively more gas daily than they do in summer. The most gas is consumed by households in winter as would be expected. The seasons capture the additional unobserved seasonal effects on residential gas demand that are not accounted for in the weather variables.

The coefficient on the treatment group dummy is insignificant, verifying that the households were selected at random to take part in the DSM stimuli and that there are no important underlying differences between the treatment group and the control group. The coefficient on the treatment period dummy and the coefficient on the interaction term representing the observations from the treatment group in the treatment period are both negative and significant. This provides strong evidence that the demand side stimuli, incorporating the increased frequency of billing, the additional usage information made available and the provision of an IHD unit and the introduction of a variable tariff, are effective in reducing household daily gas consumption, echoing the conclusions of the cost benefit analysis conducted as part of Ireland's Smart Metering Gas Consumer Behavioural Trial (CER, 2011). It is important to note that the individual treatments in the demand side stimuli were also included as dummies in a different model and none of the dummy coefficients registered any real statistical significance. However, this is most likely due to a sample size issue with each individual treatment having comparatively fewer observations in the sample than the treatments combined. More details of the individual treatment effects are presented in Chapter 3. Further-

more, as the treatment was randomly assigned, it is fair to state that the combined treatment causes a reduction in daily gas consumption by households.

Somewhat surprisingly, households with no attic insulation were found to consume less natural gas per day relative to households with attic insulation more than 5 years old. According to O'Doherty et al. (2008), households with higher incomes tend to have more energy saving features and an increase in a household's income is also associated with higher potential energy use. Therefore, as this analysis cannot control for income completely, it is possible that the omitted variable income could be biasing the coefficients on the categories of attic insulation. It is more likely that high income households have attic insulation, while they may also consume more natural gas. Households without external wall insulation consume significantly more gas compared to households with external wall insulation, highlighting the success of external wall insulation as an energy saving measure and reiterating the Brounen et al. (2012) result that insulation is a significant factor in gas consumption.

Households that never service their boilers or only service them every 2-3 years use less gas in a day than those that service their boilers every year. This is an unexpected result with a well serviced boiler likely to be more efficient and requiring less gas. On the other hand, it could be a result of reverse causality. A household that consumes a large amount of gas daily may need to have their boiler serviced more often and this would fully explain the unexpected result. The other energy saving measures (double glazed windows and a lagging jacket on the cylinder) are found not to have a statistically significant effect on household gas demand. Household ownership of a fire effects gas fire results in an increase in household daily gas use, while households that have a booster button on their gas heating system also use more gas, though its significance is much less convincing.

2.6 Conclusion

This chapter used a micro-econometric analysis of the high frequency gas consumption panel data from the Smart Metering Gas Consumer Behavioural Trial (CER, 2011) to examine the determinants of residential gas demand in Ireland. Half hourly gas consumption data collected from 1,181 household meters over 539 days was aggregated into daily gas use data, and together with the socio-economic and household level characteristics from the pre-trial survey and weather variables provided by Met Éireann, this formed a balanced panel dataset on which the analysis was conducted. A random effects estimator with cluster robust standard errors clustered at the household level

was used to estimate the model.

The number of household members and the age of the house are found to have a strongly positive association with residential gas demand in Ireland. Households in detached houses and bungalows are found to use more gas relative to their counterparts in semi-detached houses, which could be due to the fact that their building walls are mostly external. The size of the house, controlled for by using number of bedrooms as a proxy, is also a key determinant, with households in larger houses in Ireland consuming significantly more gas on average. Additionally, tenure is also shown to be an important factor for household gas demand. Another finding from the analysis is that homeowners consume more gas than renters; however, this may be a result of an underlying income effect as a large proportion of the homeowners in the sample own their houses outright and, as a result, likely have more disposable income to spend on gas.

All the weather variables controlled for in the analysis are found to be highly significant in determining residential gas demand. As expected, heating degree days, a measure of the impact of temperature on the heating requirement, is shown to have a strong positive association with household daily gas consumption. The four season variables, which capture any additional seasonal effects not accounted for by the weather are also significant determinants, with the most household gas consumed in the winter season relative to the summer season. Moreover, it is found that households consume more gas on public holidays and weekends when there are usually more people at home.

Overall, this chapter has shown that the socio-economic characteristics of the households, together with the dwelling characteristics and energy efficiency measures, are highly significant determinants of residential gas demand in Ireland. Furthermore, weather is found to be the most influential factor on a household's daily gas consumption and for that reason should be included in any gas demand forecasting model.

The demand side stimuli tested as part of the smart metering trial's DSM programme to influence consumers to use less gas are found overall to be effective at reducing household daily gas consumption and reaffirms the conclusion of the CER (2011) report. These stimuli were essentially informational in nature: households in the treatment groups were given more information about their gas use, some were given monthly rather than bi-monthly bills and others were provided with extra information through in-home electronic displays. Reductions in demand due to improved information may suggest that households better understood their energy use, and thus could optimise it better, or that the measures made the costs of use more salient. Unfortunately, due to limited sample sizes, the effectiveness of each individual stimulus could not be tested with much confidence.

Chapter 3

Heterogeneity and Habit Formation in the Effect of Demand Side Management Stimuli on Residential Gas Demand[1]

3.1 Introduction

Demand side management (DSM) is a mechanism increasingly employed by energy suppliers and policymakers to promote behavioural change in the energy consumption of households and to contribute to carbon abatement targets and climate change mitigation. As described in Chapter 2, such programmes allow households a greater role in reducing their energy consumption and shifting their demand for energy during peak periods by either improving the information available on potential energy efficiency opportunities or by giving a financial incentive to decrease their overall energy use. The evolution of 'smart metering'[2] has made DSM more effective by increasing the frequency and availability of information feedback on residential energy consumption and giving households the greatest opportunity to manage and conserve their energy use.

The full rollout of natural gas and electricity smart meters in Ireland is currently scheduled by the Commission for Energy Regulation (CER) to commence in 2019 with all installations expected to be completed in 2024. While the benefits of electricity smart metering are apparent, where consumers are provided with a mechanism to shift

[1]The research presented in this chapter is under review at *Energy Economics*.

[2]Smart meters provide two-way communication to households and energy suppliers of actual household energy consumption at regular intervals, for example, every half hour.

their electricity usage away from peak consumption times when electricity production is much more expensive, the benefits of natural gas smart metering are less obvious, as the marginal cost of increased gas flow is considerably lower compared to electricity during peak demand. In fact, the one main advantage of natural gas smart metering is often cited as its potential to help with energy efficiency and carbon abatement, since it provides information feedback to consumers of their actual gas usage, allowing them to avoid unnecessary consumption and cost, and as a result help reduce environmental damage.

Utilising a difference-in-differences methodology in Chapter 2, it was established that the DSM stimuli enabled through smart metering and employed in Ireland's Gas Consumer Behavioural Trial reduced daily household gas use on average. The results found that the average treatment effect (ATE) was a reduction in household natural gas consumption of 1.54 kilowatt-hours (kWh) per day, and with a consumer base of over half a million gas using households in Ireland, these energy savings are economically significant and contribute meaningfully to carbon abatement. However, to realise the full potential of natural gas smart metering it is important for suppliers and policymakers to understand how the ATE varies across different socio-economic and household level factors. For example, are most of the energy savings from such stimuli to be gained from households with a certain set of characteristics? Furthermore, it is also necessary to establish if the stimuli induce habit formation in households. If the information provided through the stimuli cause households to change their behaviour and decrease gas usage, it is important that this is not only in response to the novelty of additional information and rather that the change is persistent across time.

Within this context, the objective of this chapter is to explore the heterogeneous treatment effects (HTEs) of the DSM stimuli employed in the Smart Metering Gas Consumer Behavioural Trial using a micro-econometric analysis. More specifically, it examines the heterogeneity in the ATE, estimated in Chapter 2, across different groups of households categorised by their socio-economic, household level and dwelling characteristics. It is the first study to consider heterogeneity in the effect of DSM stimuli across such a broad range of household characteristics and the only analysis internationally to reflect such heterogeneity in the case of residential gas demand. This chapter also estimates the average impact of the demand side stimuli over the bimonthly billing cycles in the trial to observe any evidence that the stimuli were habit forming. Additionally, it investigates the quantile treatment effects (QTEs) across the whole distribution of daily gas consumption and compares the short run and long run ATE in a dynamic model.

The remainder of the chapter is structured as follows. In Section 3.2 the related literature is reviewed. In Section 3.3 the data is described. Section 3.4 outlines the details of the models specified and the estimators used. Section 3.5 presents the results of the analysis and Section 3.6 concludes the chapter.

3.2 Literature

Much of the literature examining the impact of smart metering assisted DSM is focused on the effect of information feedback on residential energy use. For example, in a review of the international literature on the effectiveness of feedback on gas and electricity consumption, Darby (2006) established that while feedback is necessary for residential energy reduction, it is not always sufficient as households need help in interpreting their feedback and deciding on what actions to take. The author reports energy savings for the literature reviewed in the range of 5-15% and 0-10% for direct and indirect feedback respectively. Most recently, Ramos et al. (2015) undertook a comprehensive review of the empirical evidence on the impacts of energy efficiency policies in the residential sector with a specific emphasis on the effect of information and feedback mechanisms on energy use and they found that feedback programs demonstrated energy savings of around 2-3%. Their analysis revealed that the frequency at which the feedback is delivered is an important determinant of its success in reducing consumption. They identify that while energy bills are not that frequent, smart meters have a greater potential to provide real-time information and such instruments have achieved energy savings up of to 15% in some studies, similar to the findings of Darby (2006).

In another review of empirical studies to help determine evidence for which kinds of feedback are most successful in reducing electricity consumption, Fischer (2008) cover 26 projects in 10 countries in the period from 1987 to 2006. They concentrate on programs designed to give direct feedback and that have an effect on overall consumption as opposed to load shifting. Most notably, the review identifies many characteristics of successful feedback, such as actual consumption, frequency, interaction, and appliance specific breakdown, with the authors suggesting that smart metering is an "especially useful tool" in adopting such features. Indeed, the overall finding in Jessoe and Rapson (2014) suggested that providing residential electricity users with real time information about their energy usage, enabled through In-House Displays (IHDs), increased their price elasticity of demand. In analysing a dozen utility pilot programs using IHDs to promote energy conservation, Faruqui et al. (2010) found that feedback provided by IHDs leads to a decrease in a household's average electricity use by about 7% and when

combined with a prepayment system the impact is doubled. Delmas et al. (2013) echoed these findings in a meta-analysis of information-based energy conservation experiments from 156 published field trials from 1975 to 2012. They estimated a reduction in average electricity use of 7.4% as a result of the provision of such information and argued that "experiments in energy conservation should use dedicated control groups, take sufficient baseline measurements and control for weather and demographic characteristics".

In addition to the above general reviews of the influence of information feedback on energy use, there are many standalone research studies which employ randomized control experiments to estimate the treatment effect of feedback on energy demand and more specifically on electricity use. For example, Attari et al. (2014) used such an experiment from a New York apartment building to estimate the effects of feedback from an IHD, which gives near real-time plug level information on electricity use. They estimated the outcome to be a 12-23% reduction in electricity use in treated apartments with the authors suggesting that in contrast to the majority of the literature, the reductions are as a result of factors such as salience or a Hawthorne effect[3], rather than the real-time information. For Ireland, Carroll et al. (2014) examined data from a randomized controlled smart metering electricity trial and showed that smart metering enabled feedback leads to a decrease in household electricity demand, while households treated with the feedback also increased their self-reported stock of energy-saving information. However, the authors established no correlation between the improved stock of self-reported information and the electricity demand reductions, thus concluding that"smart metering is effective because it acts as a reminder and motivator, rather than an educational aid". In another field experiment, Delmas and Lessem (2014) installed energy meters in the residence hall rooms of the University of California, Los Angeles and provided the students from a number of these rooms with private information on their electricity usage, in the form of real-time feedback. They also made the energy usage of a subset of these rooms public, in the form of posters. Their results showed that when private information was combined with public information, average energy savings of 20% were achieved, with most of the savings coming from high energy users.

There is a very limited body of research examining the HTEs of feedback on energy consumption across different socio-economic and dwelling characteristics. Fischer's (2008) review of empirical evidence advised that "there is probably not "the" perfect feedback for everybody" and found that complex feedback tools may not be as effective

[3]The Hawthorne effect refers to the alteration of an individual's behaviour as a result of their awareness of being observed in a study.

for households with lower education or elderly people, while Abrahamse et al.'s (2005) review of intervention studies recommended that the effectiveness of interventions and the possible determinants of behaviour should be examined simultaneously. In a study of almost 5,000 households across 11 European countries, Mills and Schleich (2012) established that families with young children are found to be more likely to use energy conservation practices in the home, while elderly households are less likely to adopt conservation strategies. They also found that education levels lead to greater variation across household energy saving behaviour with higher levels of education associated with strong positive impacts on household use of energy conservation practices. Given the increasingly ageing population, Barnicoat and Danson (2015) explained that there is a need to understand the attitudes and behaviours of older age groups with respect to smart energy conservation. Their interviews with older people in Scotland revealed that they had concerns about the IHD not providing any knowledge on where energy savings could be made and they also expressed confusion over what the information given to them actually meant.

Considering the effect of customized and adaptive consumption feedback on the energy use behaviour of low income households in the Mediterranean region, Podgornik et al. (2016) demonstrated that low income households exposed to contextualised feedback have electricity savings of between 22-27%. They also found that these households are more inclined to view monitoring as an invasion of their privacy. In the UK, Dolan and Metcalfe (2015) found no significant heterogeneous effect for the wealth and gender of the head of household in their study on the impact of social norm feedback on energy consumption, though their results indicated that households with larger dwellings are less likely to reduce their energy use as a result of the feedback. Asensio and Delmas (2016) examined how framing interventions can affect energy consumption over time using an appliance level feedback field experiment in a housing complex in Los Angeles and they showed that adapted information about the environmental and health consequences of residential electricity consumption can be more useful in helping households reduce their energy compared to cost salience in framing the conservation effort.

There are some studies that examine heterogeneity in the treatment effect of other environmental policies, such as Ferraro and Miranda (2013). They investigated the HTEs of a large scale field experiment conducted in partnership with a water utility in Atlanta USA in 2007 to encourage reductions in household water usage. They provided evidence that households that are wealthier, owner occupied and use more water are much more responsive to strong norm feedback, which augments technical information with pro-social language and social comparisons. There was no real evidence of

HTEs for information with no social comparison and they determined that information on heterogeneous responses is necessary "to improve the programs cost effectiveness through more precise targeting of messages using publicly available data". Wichman et al. (2016), in their panel analysis of monthly water consumption for 1,727 households residing in detached, single-family homes located in six North Carolina municipalities, provided strong evidence that prescriptive conservation interventions have favourable effects across socio-economic groups relative to pricing policies and also lead to reductions among high water users.

Another strand in the literature considers differential effects of feedback for high and low consumers of energy with Fischer's (2008) review acknowledging that high energy using customers responded differently to feedback compared to low consumption customers, while Abrahamse et al.'s (2005) review found that sometimes the latter group increased their energy use as a result of a conservation intervention. However, Allcott's (2011) investigation into the effects of the OPOWER home energy reports in the US found, using a quantile regression methodology, that the treatment effect increases along the overall distribution of energy consumption and that not even the low consumption households increased their usage in response to the feedback, which provides evidence against the documented 'boomerang effect' of Schultz et al. (2007). In another quantile study, Schleich et al. (2013) econometrically tested the effectiveness of feedback on electricity consumption in a field trial carried out on more than 1,500 households in Linz, Austria and their results showed that feedback has no effect on households below the 30th quantile and above the 70th quantile of the electricity consumption distribution.

Some of the literature in this area examines the impact of feedback on household energy consumption over time and provides evidence that helps identify whether or not information feedback is habit forming. For instance, Kniesner and Rustamov (2015) examined the magnitude of the effect of a residential energy efficiency audit program in California, which gave households feedback on their energy use behaviour and provided energy saving tips. They found the program to be effective in reducing electricity consumption and suggested that the "effects become significant and increase in magnitude gradually over time but at a decreasing level". In contrast, Allcott (2011) found no evidence of any decay in the feedback treatment effect over the two years of treatment in his study and moreover, the effects are higher in the second year than the first year of treatment with comparable weather in both years. In a study by Gilbert and Zivin (2014), where changes in household electricity consumption behaviour throughout the monthly billing cycle in San Diego were studied, the results revealed that routine billing provides households with intermittently salient information at which point the house-

hold adjusts behaviour, though over time the attention to this billing information fades and the household returns to a higher rate of energy use.

Despite all of this previous work, significant gaps relate to the overall heterogeneity and persistence in the effects of information based DSM stimuli on household energy demand. More specifically, none of the international literature explores such issues in the case of residential natural gas consumption. These issues are directly addressed in this chapter.

3.3 Data

The data used in this chapter includes daily household gas consumption in kilowatt hours (kWh) for 1,294[4] Irish households over a period of 539 days collected as part of Ireland's Smart Metering Gas Consumer Behavioural Trial (CER, 2011). Descriptive statistics for daily gas consumption for the 1,294 households are presented in Table 3.1. The mean daily gas consumption in this sample is calculated over the 18 months of the trial at 47.7kWh.

Table 3.1: Descriptive statistics for daily gas consumption.

	Mean	**St. Dev.**	**Min**	**Max**	**T**	**N**
Daily Gas Usage (kWh)	47.7	45.1	0	530.49	539	1294

As discussed previously in Chapter 2, the Smart Metering Trial was run from 1st December 2009 to 30th May 2011 and consisted of a benchmark period and a treatment period. In the benchmark period (1st December 2009 to 31st May 2010), all participants were charged their normal tariff and received bi-monthly billing in a business as usual context. Data collected during this period was for the purpose of establishing the benchmark level of use by households. In the treatment period (1st June 2010 to 30th May 2011), participants were divided into treatment and control groups. The treatment groups were placed on different DSM stimuli, which were essentially informational feedback in nature, while the control group remained on their normal tariff and had no changes to their bimonthly bill. The DSM stimuli included: providing the household with an energy usage statement along with their bimonthly bill; a more frequent bill

[4]The data includes the 1,181 households in Chapter 2 plus 113 households that were dropped from the analysis in Chapter 2 for failing to answer some key dwelling characteristic questions in the pre-trial survey relevant to that analysis.

and energy usage statement (monthly); the provision of an IHD unit; and finally, the provision of an IHD together with a variable tariff. The energy usage statement gave additional information on a household's gas usage and tips on energy reduction, while the IHD provided real time information on energy consumption and cost with accessible historical data for the previous month. The variable tariff changed with each bill with the highest tariff in the winter and the lowest tariff in the summer. The proportion of Irish households in the sample randomly assigned to each individual DSM stimuli is outlined in Table 3.2 and the proportion of households split between the control and the overall treatment group is 35% and 65% respectively.

Table 3.2: Proportion of households in treatment and control groups.

	Control %	**Treatment** %
Bimonthly Billing with Energy Usage Statement		16
Monthly Billing with Energy Usage Statement		15
Bimonthly Billing and an IHD		17
Bimonthly Billing with an IHD and Variable Tariff		17
Total	35	65

This chapter also uses the socio-economic and housing characteristic micro-data gathered in the pre-trial survey which was distributed to the participating households before the commencement of the trial, together with the daily weather data provided by Met Éireann's Dublin Airport weather station and comprising of variables on heating degree days, sunshine hours, mean cloud cover, daily rainfall and wind speed.[5] In terms of the socio-economic and housing characteristic micro-data, the proportion of households in the variable categories important to this analysis are divided between control and treatment groups and presented in Table 3.3. It is evident that there is considerable heterogeneity across households in the sample and that the treatment group is representative and comparable to the control group in this study[6].

[5]For a more detailed description of the weather variables, see Chapter 2.

[6]χ^2 tests were conducted to test for the equality of proportions between the control and treatment groups in each category and statistical differences were found only for the "Self-employed" category in Employment Status and the "Don't Know" category in Attic Insulation (see Appendix B, Table B.1).

Table 3.3: Proportion of households in the different variable categories for control and overall treatment groups.

		Control %	Treatment %			Control %	Treament %
Female		47.0	48.2	**Number of Bedrooms**			
				1-2 Bedrooms		9.0	9.9
Age				3 Bedroom	*Ref*	55.0	49.3
<36 years		14.7	14.7	4 Bedrooms		31.2	34.2
36-45 years	*Ref*	27.2	27.9	5+ Bedrooms		4.8	6.6
46-55 years		23.2	23.9				
56-65 years		14.9	17.3	**Period House Built**			
65+ years or Refused		20.0	16.2	Pre 1940		13.6	11.5
				1941-1960		11.0	10.2
Education				1961-1980		23.7	20.9
None or Primary		8.5	8.6	1981-2000	*Ref*	28.7	29.4
Junior Cert		13.2	12.3	2001-2008		23.0	28.0
Leaving Cert		23.5	22.8				
Third Level	*Ref*	48.7	52.1	***Dwelling Characteristics:***			
Refused		6.1	4.2	**Attic Insulation**			
				<5 years		25.0	27.6
Employment Status				>5 years	*Ref*	62.5	63.8
Employee	*Ref*	59.4	57.8	None		8.5	6.9
Self-employed		9.0	13.4	Don't Know		4.0	1.7
Unemployed		5.9	7.5				
Retired or Care Giver		25.7	21.3	**External Wall Insulation**			
				Yes	*Ref*	46.9	48.3
Number of Household Members				No		36.4	36.3
1 Person		18.4	15.2	Don't Know		16.7	15.4
2-3 People	*Ref*	49.6	50.8				
4+ People		32.0	34.0	**Boiler Service**			
				Never		8.1	9.5
Tenure (Rented)		8.3	6.1	Every 2-3 years		36.6	35.6
				Every year	*Ref*	55.3	54.9
House Type							
Apartment or Terraced		23.9	22.9	**Double Glazing**		93.2	94.5
Semi-Detached	*Ref*	55.5	55.4	**Lagging Jacket**		89.7	88.5
Detached or Bungalow		20.6	21.7	**Booster Button**		40.4	41.1
				Fire Effects Gas Fire		48.0	44.9

Note: *Ref* is the omitted reference category.

3.4 Methodology

The starting point here is a variant of the model in Chapter 2 which estimates the ATE of the DSM stimuli employed in Ireland's Smart Metering Gas Consumer Behavioural Trial using a difference-in-differences methodology, such that:

$$G_{it} = \alpha_i + \lambda_t + \beta D_{it} + \epsilon_{it} \tag{3.1}$$

where the dependent variable G_{it} represents the daily natural gas demand of household i at time t. α_i is the treatment group fixed effect, λ_t is the treatment period fixed effect and the parameter of interest β is the average causal effect of the DSM stimuli on a household's daily gas consumption, with D_{it} denoting the interaction term that indicates observations from the treatment group in the treatment period. ϵ_{it} is the idiosyncratic error term. For baseline estimation in this chapter, Model (3.1) is estimated using the ordinary least squares estimator with cluster robust standard errors clustered at the household level. A model is also estimated to establish the effect of each of the individual demand side stimulus on a household's daily gas demand. This model is as follows:

$$G_{it} = \sum_{k=1}^{4} \alpha_{ki} + \lambda_t + \sum_{k=1}^{4} \beta_k D_{kit} + \epsilon_{it} \tag{3.2}$$

where k are the individual demand side stimuli from treatment 1 to 4 and β_k are the causal impacts of each of the individual treatments on a household's daily gas consumption. In this chapter and in contrast to Chapter 2, the full results of the impact of each individual stimulus will be reported. The primary aim of these estimations is to provide a starting point for the main goal of this research, which is to investigate the treatment effect heterogeneity of the DSM stimuli employed in the smart metering trial.

To investigate the HTEs of the DSM stimuli on daily residential gas demand across different groupings, the ATEs are allowed to vary systematically across the socio-economic and household level characteristics in a structural model, such that:

$$G_{it} = \alpha_i + \lambda_t + \beta D_{it} + \theta X_i + \Theta X_i * D_{it} + \gamma Y_i + \Gamma Y_i * D_{it} + \pi Z_i + \Pi Z_i * D_{it} + \delta W_t + \epsilon_{it} \tag{3.3}$$

Here, $X_i{*}D_{it}$ is a vector of the socio-economic characteristics of the chief economic supporter (CES) in the household interacted with the treatment dummy. $Y_i{*}D_{it}$ are the household level characteristics interacted with the treatment dummy and $Z_i{*}D_{it}$ are the dwelling energy characteristics (booster button, external wall insulation, double glazing

etc.) interacted with the treatment dummy. W_t represents the weather variables, including heating degree days, rainfall, sunshine hours, cloud cover and wind speed. The interaction terms will establish whether the ATE differs across groupings e.g. are the ATEs the same for households that live in a detached house compared to households that live in a bungalow. The model also includes the main effects from the socio-economic, household level and energy characteristics and is estimated using a random effects estimator with cluster robust standard errors clustered once again at the household level. The random effects estimator is utilised instead of the fixed effects estimator, to estimate coefficients for the categorical and binary variables in the model that do not change over time.

Additionally, to study the ATE across time and to examine whether the demand side stimuli are habit forming, the entire period is divided into nine bimonthly billing cycles. Each of the cycles was calendarised in the trial, so that a billing cycle would contain exactly two calendar months for all consumers. Billing cycles one to three are in the control period and cycles four to nine are in the treatment period. All cycles are interacted with the treatment group dummy and billing cycle one (December 2009/January 2010) is omitted as the base category. The fixed effects model below is then estimated with cluster robust standard errors at the household level:

$$G_{it} = \alpha_i + \sum_{c=2}^{9} \lambda_c + \sum_{c=2}^{9} \beta_c D_{ic} + \epsilon_{it} \tag{3.4}$$

where β_c is the ATE of the demand side stimuli for billing cycle c relative to the control group in all cycles with the treatment group in billing cycle one. The main effects of the interaction terms are also included in this regression.

Furthermore, quantile regressions are estimated to explore the variability in treatment effects across the distribution of daily residential natural gas consumption i.e. to calculate the QTE. In particular, the pth quantile regression estimators α_i^p, λ_t^p and β^p are chosen to minimize:

$$p \sum_{G_{it} \geq \alpha_i^p + \lambda_t^p + \beta^p D_{it}} |G_{it} - \alpha_i^p - \lambda_t^p - \beta^p D_{it}| + (1-p) \sum_{G_{it} < \alpha_i^p + \lambda_t^p + \beta^p D_{it}} |G_{it} - \alpha_i^p - \lambda_t^p - \beta^p D_{it}| \tag{3.5}$$

where $0 < p < 1$. In this analysis, quantile regressions are estimated at each decile of the daily household gas consumption distribution, implying $p = 0.1, 0.2, ..., 0.9$. The coefficients are estimated by implementing a difference-in-differences approach in the quantile regressions with cluster robust standard errors at the household level. QTE estimates will help us understand the heterogeneous impacts on different points of the

outcome distribution. A detailed discussion on quantile regression analysis is presented in Chapter 4.

Finally, the short and long run ATEs are estimated using a dynamic partial adjustment model:

$$G_{it} = \alpha_i + \beta D_{it} + \theta G_{it-1} + \epsilon_{it} \tag{3.6}$$

Since past gas consumption can be seen as a time varying confounder to the treatment response that cannot be subsumed in a time-invariant variable like α_i, this model controls for the dynamic nature of gas consumption by including a lagged dependent variable on the right hand side. From this model, assuming β is negative and θ is positive, the impact of the demand side stimuli is to reduce daily household gas consumption on average by β today (the short run ATE). Then, in period $t+1$ gas consumption will continue to decrease with past consumption having a positive effect ($\beta\theta$) and the long run ATE can be shown to be equal to $\beta/(1-\theta)$. Model (3.6) is estimated using both OLS and fixed effects regression with cluster robust standard errors at the household level. In this instance, the fixed effects estimator can suffer from Nickell bias, where the estimate of the coefficient for the lagged dependent variable is biased due to the correlation between the regressor and the error term as a direct result of the demeaning process. However, the bias is decreasing in T, and with T equal to 539 here, the bias is much less of a concern and thus a fixed effects estimator is employed.

3.5 Results

The baseline estimated results from Model (3.1) are presented in Table 3.4. The ATE is statistically significant at the 5% level and to give an intuitive sense of the average daily gas savings, 1.63kWh is roughly equivalent to leaving the smallest ring on a gas cooking hob on full for a little over an hour.[7] As a further robustness check, a simple comparison of means between treatment and control household's during the treatment period shows a statistically significant lower mean gas usage for the treated households compared to the control.

Table 3.4: Estimated ATE from the difference-in-differences model of daily gas usage.

VARIABLES	Daily Gas Usage	Std. Errors†
λ_t	-22.958***	0.565
α_i	0.881	1.578
D_{it}	-1.635**	0.721
Observations		697,466
Number of ID		1,294

†Cluster robust std. errors at the household level
***p<0.01, **p<0.05, *p<0.1

For the individual demand side stimuli (Model (3.2)), the results in Table 3.5 present no real statistically significant effect for each of the individual stimulus due most likely to a sampling size issue with just around 200 households per individual treatment. However, all the coefficients are negative and economically significant, ranging from -1.50 to -1.78, though only the bimonthly energy usage statement and monthly energy usage statement are borderline statistically significant at the 10% level. This provides some evidence that all demand side stimuli have similar ATEs and play an important role in the overall ATE with none of the stimuli found to have different effects from each other.

[7]Including the 113 additional households that were dropped in Chapter 2 has increased the ATE of the demand side stimuli marginally from 1.54 kWh to 1.63 kWh in gas savings for a household per day.

Table 3.5: Estimated individual ATEs from the difference-in-differences model of daily gas usage.

VARIABLES	Daily Gas Usage	Std. Errors†
λ_t	-22.958***	0.565
Bimonthly Usage Statement$_i$	2.241	2.374
Bimonthly Usage Statement$_{it}$	-1.783*	1.079
Monthly Usage Statement$_i$	1.285	2.311
Monthly Usage Statement$_{it}$	-1.780*	1.036
Bimonthly Usage Statement and IHD$_i$	0.412	2.269
Bimonthly Usage Statement and IHD$_{it}$	-1.501	1.000
Bimonthly Statement, IHD and Variable Tariff$_i$	-0.287	2.293
Bimonthly Statement, IHD and Variable Tariff$_{it}$	-1.500	1.113
Observations		697,466
Number of ID		1,294

†Cluster robust std. errors at the household level
***p<0.01, **p<0.05, *p<0.1

In terms of the results for the HTEs, there is substantial evidence that the demand side stimuli have very different effects across socio-economic, household and dwelling characteristics; see Table 3.6. This evidence is provided by the coefficients on the interaction terms in Model (3.3).[8] The ATE is found to be heterogeneous over the age category of the CES in the household with the stimuli being more effective in households with older CESs (46-55 years and 56-65 years old), and less effective on households with younger CESs (<36 years old). This could be because households with older residents are likely to have a greater preference for heat and comfort and as a result have the greatest capacity to make savings using the information delivered in the energy usage statement or on the IHD unit.

[8]As a robustness check, HTEs were estimated for each category in individual models, unconditional on other characteristics, and the interaction coefficients were found to be of the same signs and statistical significance as the coefficients in the larger model conditional on all characteristics (see Appendix B, Table B.2).

Households with a CES educational attainment of no more than primary school are less responsive to the demand side stimuli relative to the base. The information given in the usage statements and on the IHD are purposefully made accessible to all consumers. However, it may be that those households with a low level of educational attainment may have difficulties interpreting the bar charts or are otherwise confused by, or uninterested in, the data. For employment status, the ATE differs only for households with a self-employed CES. The treatment employed in the trial is much more effective for these households with a statistically significant negative effect at the 5% significance level.

The results suggest that there are statistically significant differences in the ATE across the number of members in each household. Larger households (4+ people) respond to the demand side stimuli more successfully and have a higher average effect, while the average effect is significantly less for households with only one person. This could possibly be explained by the larger household having a greater ability to change their behaviour in response to the stimuli relative to a one person household. Renters are revealed here to be less receptive to the demand side stimuli. Renters are found to consume much less gas per day when compared to homeowners in Chapter 2 and thus it may be that they have a reduced capacity to make any further savings that haven't already been made.

In examining the dwelling characteristics, the ATE is stronger for households in detached houses and bungalows compared to other house types. Households in detached houses and bungalows are recognised in the literature as very high energy consumers due mainly to having more external walls and the additional heat loss that results. These households could pay more attention to the information received from the stimuli because they have more to gain by reducing their gas use. Also, there is considerable heterogeneity in the ATE across house size and period of house build. The number of bedrooms is a proxy for house size and the results show that the demand side stimuli have a significantly higher impact in households with more bedrooms. The ATE is larger for households in 4 bedroom and 5+ bedroom houses and considerably smaller for households in 1-2 bedroom houses, with all coefficients being statistically significant at the 1% level. For the period of house build, it is evident that households in older houses are more responsive to the treatment. Like households in detached houses and in large houses, households in old houses are known to have relatively high gas consumption. Therefore, as before, it is likely that such households have a bigger incentive to take notice of their energy use information and change their behaviour.

Interestingly, the ATE does not differ significantly across a dwellings' energy char-

acteristics; however, there are a few notable exceptions. There is a highly significant negative coefficient on the treatment group interaction with households in dwellings with no external wall insulation and a significant negative coefficient on the interaction with household ownership of a fire effects gas fire. This provides some further evidence that households with a high baseline gas use are much more receptive to the demand side stimuli. Furthermore, the results indicate that households that never service their boiler are much less responsive to the treatment. One explanation for this could be that such households have an embedded passive attitude towards their energy use which carries over into the trial. Also of relevance is that households with attic insulation installed in the last five years are found to be somewhat less responsive to the information based stimuli, which may be an indication that the recent investment in dwelling energy efficiency measures could make households pay less attention to the information provided through smart metering enabled demand stimuli. In addition, the ATE is found to be heterogeneous across the seasons with winter providing the largest increase for the ATE. The treatment is also seen to have a greater impact on weekends and public holidays.

Table 3.6: Estimated HTEs from the random effects structural model.

VARIABLES	Daily Gas Usage	Std. Errors†	VARIABLES	Daily Gas Usage	Std. Errors†
Treatment			**Period House Built*D$_{it}$**		
λ_t	-1.197***	0.438	Pre 1940	-5.824***	1.715
α_i	0.057	1.306	1941-1960	-3.217**	1.526
D$_{it}$	9.276***	2.834	1961-1980	-4.025***	1.198
			1981-2000	*Ref*	
Female*D$_{it}$	-1.087	0.809	2001-2008	-1.258	0.901
Age*D$_{it}$			**Weather**		
<36 years	2.149**	0.985	Heating Degree Days	4.695***	0.057
36-45 years	*Ref*		Sunshine Hours	-1.033***	0.018
46-55 years	-2.501**	1.100	Cloud Cover	0.841***	0.031
56-65 years	-3.136**	1.316	Rainfall	0.146***	0.009
65+ years or Refused	-2.334	2.167	Wind Speed	0.935***	0.014
Education*D$_{it}$			**Time*D$_{it}$**		
None or Primary	2.417*	1.400	Weekend Day	-0.765***	0.171
Junior Cert	-0.539	1.311	Public Holiday	-2.499***	0.465
Leaving Cert	0.558	0.905	Winter	-2.800***	1.153
Third Level	*Ref*		Spring	-1.252***	0.659
Refused	-1.251	2.246	Autumn	-1.456***	0.309
Employment Status*D$_{it}$			**Dwelling Characteristics*D$_{it}$**		
Employee	*Ref*		Double Glazing	-1.592	1.966
Self-employed	-2.470**	1.144	Lagging Jacket	-0.548	1.089
Unemployed	1.588	1.308	Booster Button	0.211	0.822
Retired or Care Giver	-1.853	1.769	Fire Effects Gas Fire	-1.257*	0.764

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Table 3.6 – continued from previous page

VARIABLES	Daily Gas Usage	Std. Errors†	VARIABLES	Daily Gas Usage	Std. Errors†
No. of Household Members*D$_{it}$			**Attic Insulation*D$_{it}$**		
1 Person	3.865***	1.197	<5 years	1.503*	0.914
2-3 People	*Ref*		>5 years	*Ref*	
4+ People	-1.863**	0.849	None	1.795	1.599
			Don't Know	2.871	2.473
Tenure*D$_{it}$ (Rented)	3.510***	1.282			
			External Wall Insulation*D$_{it}$		
House Type*D$_{it}$			Yes	*Ref*	
Apartment or Terraced	1.298	0.981	No	-3.537***	1.020
Semi-Detached	*Ref*		Don't Know	-0.657	1.043
Detached or Bungalow	-2.494**	1.013			
			Boiler Service*D$_{it}$		
Number of Bedrooms*D$_{it}$			Never	2.346*	1.286
1-2 Bedrooms	4.497***	1.212	Every 2-3 years	0.907	0.848
3 Bedrooms	*Ref*		Every year	*Ref*	
4 Bedrooms	-5.250***	0.944			
5+ Bedrooms	-12.327***	2.027	**Constant**	-23.098***	3.814
			Observations		697,466
			Number of ID		1,294
			R^2		0.582

†Cluster robust std. errors at the household level
***p<0.01, **p<0.05, *p<0.1

Table 3.7: Estimated ATE across billing cycles from the fixed effects model (3.4).

VARIABLES	Daily Gas Usage	Std. Errors†
Billing Cycle 2 (Feb/Mar 2010)	-16.294***	0.582
Billing Cycle 2*D_i	-0.348	0.719
Billing Cycle 3 (Apr/May 2010)	-57.686***	1.191
Billing Cycle 3*D_i	-1.849	1.523
Billing Cycle 4 (Jun/Jul 2010)	-80.110	1.593
Billing Cycle 4*D_i	-2.378	2.027
Billing Cycle 5 (Aug/Sep 2010)	-76.585***	1.521
Billing Cycle 5*D_i	-2.474	1.940
Billing Cycle 6 (Oct/Nov 2010)	-37.608***	0.952
Billing Cycle 6*D_i	-2.396**	1.198
Billing Cycle 7 (Dec 2010/Jan 2011)	1.127	0.751
Billing Cycle 7*D_i	-2.019**	0.909
Billing Cycle 8 (Feb/Mar 2011)	-30.241***	0.864
Billing Cycle 8*D_i	-1.933*	1.118
Billing Cycle 9 (Apr/May 2011)	-64.7183***	1.348
Billing Cycle 9*D_i	-3.030*	1.741
Constant	88.721***	0.538
Observations		697,466
Number of ID		1,294
R^2		0.443

†Cluster robust std. errors at the household level
***p<0.01, **p<0.05, *p<0.1

To further examine the heterogeneity of the ATE across the period, the results of Model (3.4) are presented in Table 3.7. These results are relative to the base group (the control group in all cycles with the treatment group in billing cycle one) and there is some strong evidence of differences in the ATE across the nine billing cycles. As expected, the treatment group in the second and third billing cycle show no sta-

tistically significant differences in ATE compared to the base group. This is because the DSM stimuli did not begin until the start of the fourth billing cycle and this confirms that through random selection the treatment and control groups have very similar gas consumption before the commencement of the treatment in the trial. Somewhat surprisingly, the treatment group in billing cycles four and five also demonstrate no statistically significant difference in ATE, though the coefficients are negative and larger in magnitude than the previous cycles.

In contrast to other research on such stimuli, it seems as though there is no immediate 'novel' effect of the treatment on a household's energy consumption and the non-significance here may indicate an initial learning or adjustment period to the demand side stimuli. By billing cycle six, the results show a statistically significant difference in the ATE compared to the base group and the coefficients register statistical significance in all cycles thereafter. The effects are persistent (though diminish in magnitude) through billing cycles six to eight while in billing cycle nine the magnitude increases again to above the initial effect reported in cycle six. This may be enough evidence to suggest that the stimuli induced habit forming behavioural change with the effect being reasonably persistent after an initial adjustment period. Furthermore, as the winter of 2010/2011 was a rare weather event in Ireland that brought heavy snowfalls and record low temperatures over a prolonged period, the increase in the magnitude of the ATE in billing cycle nine could indicate that households were forced into paying more attention again to their energy usage statements and IHD units as a result of the extreme weather. The temporal pattern of the estimated ATEs can be clearly seen in Figure 3.1.

In exploring the HTEs across groups, it was apparent that household level characteristics associated with high gas usage were the same characteristics of the households more responsive to the DSM stimuli. Therefore, in order to further investigate the hypothesis that high gas consumers are more likely to have higher treatment effects, a comparison of the treatment effects across the whole distribution of daily gas consumption is made using a difference-in-differences quantile regression approach. The results from Model (3.5) given in Table 3.8 lend some support to the hypothesis. Comparing the treatment effects estimates across the distribution of daily gas consumption, it is clear that the stimuli have no statistically significant effect in the lower quantiles (deciles 1 and 2). Thus, lower gas consumption households are not as affected by the treatment. It could be that these households are already sufficiently energy efficient or in the more likely case, they may be consuming less thermal comfort than they would like given their constrained incomes and therefore, just knowing more about how much

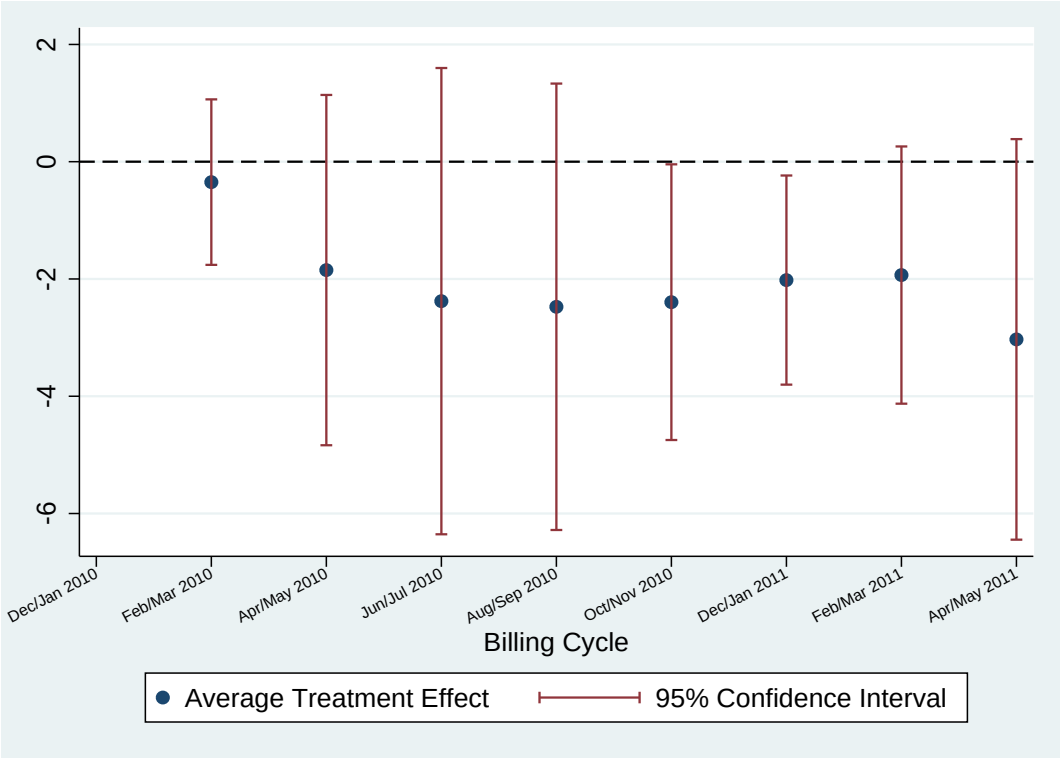

Figure 3.1: Estimated ATEs and their 95% confidence intervals across billing cycles and relative to the Dec/Jan 2010 cycle.

gas they consume is unlikely to encourage them to consume less. In higher quantiles there is a little variation in the magnitude of the treatment effects with the effect likely to increase as the household moves up the distribution of daily gas consumption (deciles 3 to 8), though the increase is not monotonic. This lends some support to the view that higher gas users have a greater capacity to make changes to their consumption patterns and as such tend to give more consideration to the demand side stimuli. However, it should be emphasised that none of these QTEs are statistically different to the baseline average effect. Furthermore, the QTE at the ninth decile was not statistically significant, implying that the households with the very highest gas consumption were not as receptive to the stimuli. Figure 3.2 plots the treatment effects and their 95% confidence intervals across the quantiles. It also shows the ATE in the continuous black line together with its 95% confidence interval in the dashed lines.

Table 3.8: Estimated QTEs from the difference-in-differences model (3.5).

VARIABLES	Daily Gas Usage	Std. Errors†	VARIABLES	Daily Gas Usage	Std. Errors†
q(.1)			**q(.6)**		
λ_t	-8.639***	1.090	λ_t	-29.218***	0.709
α_i	-1.248	1.432	α_i	0.452	1.683
D_{it}	1.248	1.372	D_{it}	-1.649*	0.919
q(.2)			**q(.7)**		
λ_t	-19.218***	0.843	λ_t	-27.966***	0.718
α_i	-0.531	1.251	α_i	0.888	1.888
D_{it}	-0.876	1.048	D_{it}	-1.948**	0.927
q(.3)			**q(.8)**		
λ_t	-24.981***	0.820	λ_t	-26.638***	1.031
α_i	0.220	1.350	α_i	1.376	2.477
D_{it}	-1.840*	1.032	D_{it}	-2.132*	1.261
q(.4)			**q(.9)**		
λ_t	-28.287***	0.889	λ_t	-26.177***	1.160
α_i	0.385	1.517	α_i	2.227	3.206
D_{it}	-1.752	1.089	D_{it}	-1.567	1.508
q(.5)					
λ_t	-29.523***	0.802			
α_i	0.476	1.599			
D_{it}	-1.879*	1.011			
			Observations		697,466
			Number of ID		1,294

†Cluster robust std. errors at the household level
***p<0.01, **p<0.05, *p<0.1

For the short run and long run ATEs, the results from Model (3.6) in Table 3.9 show that the short run effect is very different to the long run effect with slight differences between the OLS and fixed effects regressions. It is apparent that residential gas consumption is strongly related to past consumption and there is a high degree of persistence in gas demand. Controlling for a lag of daily gas consumption allows for

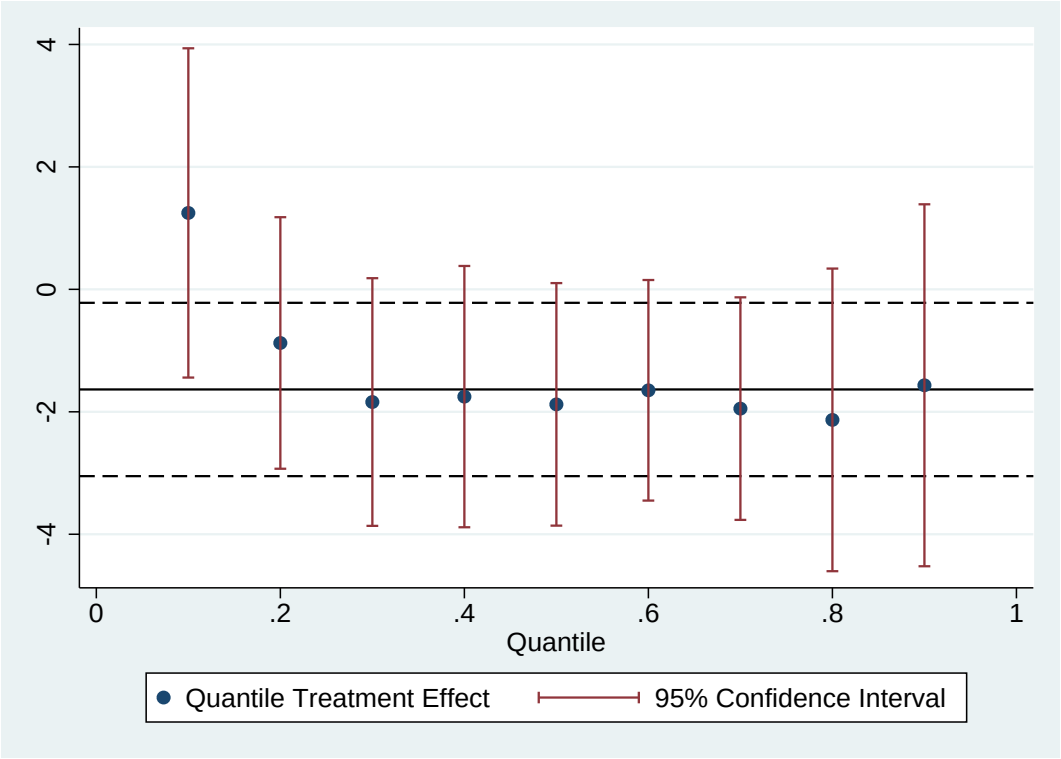

Figure 3.2: Estimated QTEs and their 95% confidence intervals.

the estimation of the causal effect of the demand side stimuli today independent of this persistence with the resultant coefficient being the short run estimate of the ATE (-0.17** OLS and -0.22** FE). There is a small short run effect on consumption, however, due to adjustment costs, part of the desired effect will be postponed to the next period $t+1$, and so on. Since past gas consumption has a positive effect, there will be a delayed treatment effect in all other periods. The aggregate impact across all periods is the long run effect and is equal to $\beta/(1-\theta)$. The long run estimates of the ATE for OLS and FE presented in Table 3.10 are -1.57 kWh and -1.59 kWh respectively and very close to the baseline ATE (-1.63 kWh) estimated in the difference-in-differences model without the lagged dependent variable. Therefore, it is evident that the DSM stimuli have a bigger long term effect than the initial short term effect would suggest.

Table 3.9: Estimated ATE from the dynamic panel models of daily gas usage.

VARIABLES	OLS	Fixed Effects
Daily Gas Usage$_{t-1}$	0.893***	0.862***
λ_t	-2.131***	-2.843***
α_i	0.083	-
D_{it}	-0.168**	-0.219**
Constant	6.429***	8.459***
Observations	690,996	690,996
Number of ID	1,294	1,294
Overall R^2	0.81	0.81
	***p<0.01, **p<0.05, *p<0.1	

Table 3.10: Short and long run ATE on daily gas usage.

VARIABLES	OLS	Fixed Effects
Short Run D_{it}	-0.168**	-0.219**
Long Run D_{it}	-1.570**	-1.587**
Observations	690,996	690,996
Number of ID	1,294	1,294
	***p<0.01, **p<0.05, *p<0.1	

3.6 Conclusion

This chapter employed a micro-econometric analysis of the gas consumption and household panel data from Ireland's Smart Metering Gas Consumer Behavioural Trial to explore the heterogeneity in the ATE of the DSM stimuli. The panel data used is from 1,294 households over 539 days in the trial, while the demand side stimuli provided feedback on overall gas use to the participant households, and was delivered at different frequencies (monthly or bimonthly) or by different mechanisms (energy usage

statement or IHD). The HTEs are examined by allowing the ATE of the overall stimuli to vary systematically across the socio-economic, household level and dwelling characteristics in a structural model and using a random effects estimator with cluster robust standard errors, clustered at the household level.

The demand side stimuli are found to have very different effects across the socio-economic characteristics of the households. The stimuli are shown to be more effective in households with an older CES and less effective in households with a CES aged under 36. For educational attainment, those households with a CES that has no more than a primary education are found to be somewhat less responsive to the stimuli. For employment status, households with a self-employed CES are considerably more receptive to the demand side stimuli and reduced their gas consumption by more relative to their base category. Moreover, this chapter provides evidence that larger households have a better ability to change their gas consumption behaviour with households comprising of four or more members found to be more responsive to the stimuli on average. Renters are found to be significantly less receptive to the consumption feedback in this study.

In other findings, the ATEs are most heterogeneous across the dwelling characteristics of the households with the feedback discovered to have a higher impact on households in older and larger houses. The average effect on residential gas consumption is found to be strongest in houses with four or more bedrooms and houses built in the pre-1940 period. Interestingly, households living in house types with more external walls, i.e. detached houses and bungalows, are also established to be more responsive to the stimuli in this analysis. The average effects of the feedback are less heterogeneous across dwellings' energy characteristics, though the most notable exception is related to the external wall effect mentioned above, with households in houses that have no external wall insulation found to be significantly more receptive to the stimuli compared to the base.

This chapter also studied the effect of the overall demand side stimulus across time, with the ATE allowed to vary over the nine bimonthly billing cycles in the period in order to identify whether the information feedback on household gas consumption was in effect habit forming. The results indicated that there is an initial learning or adjustment period to the feedback stimuli of approximately two bimonthly billing cycles and thereafter, the effects are found to be more pronounced and persistent (though diminishing) through the remaining billing cycles. This provides evidence that the feedback stimuli employed in the trial have a habit forming effect on residential gas consumption behaviour. It is of particular note that in the final billing cycle of the trial period and following a rare and sustained period of low temperatures, the average

effect was found to have increased in magnitude relative to all the other cycles. This may confirm that households were induced into paying more attention to their feedback as a result of the adverse weather shock. This chapter also employed a dynamic partial adjustment model to estimate the short and long run ATEs with the evidence suggesting that the feedback stimuli have a larger long run effect than the initial short run effect indicates.

In addition, QTEs of the feedback were also estimated in this analysis. It was evident from the HTEs that the characteristics associated with a high baseline gas use in the related literature, for example older and larger houses, are the same characteristics across which the consumption feedback was found to be generally more effective. Thus, a quantile regression methodology was used to examine any variability in the treatment effects across the distribution of daily residential natural gas consumption. The results showed that the feedback has no statistically significant effect on a household's gas consumption in the lower quantiles or in the top quantile (ninth decile), with a little variation found in the treatment effect for the other quantiles. None of the QTEs were revealed to be statistically different to the ATE.

In general terms, this chapter has shown that there is considerable heterogeneity in the effect of the DSM stimuli on residential gas demand across a household's socio-economic, household level and dwelling characteristics and specifically, there are more energy savings and carbon emissions reduction to be gained by targeting the feedback stimuli on households with the most amenable characteristics. Furthermore, the feedback stimuli used in the trial were found to have persistent effects in reducing residential gas consumption over time, with the results demonstrating that the longer term feedback effect is much bigger than the short term effect. This provides strong evidence that the stimuli did indeed induce habit formation in households and that such stimuli are effective in encouraging energy conservation over time. Finally, some evidence was found to support a slight variation in the effect of the feedback across the distribution of daily residential gas consumption with low consumption households found to have no significant response to the stimuli.

Chapter 4

The Income Elasticity of Household Energy Demand: A Quantile Regression Analysis[1]

4.1 Introduction

The main parameter of interest in the relationship between energy expenditure and income is the income elasticity of energy demand. This elasticity, which measures the percentage increase in energy expenditure given a one percent increase in income, is frequently used in models predicting future energy demand and for examining the effect of tax or subsidy policies affecting the residential sector. Examples of such policies include income support mechanisms and schemes to provide energy efficiency upgrades to dwellings, which aim to assist vulnerable households subject to fuel poverty. Moreover, for policymakers with an interest in reducing carbon emissions, the elasticity can be a useful parameter in estimating the effects of a carbon tax. In addition to these common uses, Sorrell et al. (2009) explain that many studies provide elasticity estimates as proxy measures of the so called 'rebound effect'. The rebound effect arises where improved dwelling energy efficiency lowers the cost of using household energy goods and, therefore, results in an increase in household energy consumption. If energy efficiency measures are installed and this reduces the cost of energy such that a household's real income rises, then the income elasticity would measure the impact of a rise in real incomes on energy expenditure and, under certain assumptions, present a relevant proxy for the direct rebound effect.

[1]The research presented in this chapter is published as Harold et al. (2017).

It is generally assumed in the international literature that the effect on demand of a change in average income is the main concern and, as a result, the elasticity at mean income is usually the summary statistic of most interest when examining the relationship between energy expenditure and income. However, not all policy is concerned with the average and in most cases it is more likely to target low or high energy consumption households. For example, the fuel poor are most likely in the lower left tail of the energy consumption distribution and are also primarily the target of income supports by policymakers. Therefore, the average effect of income on energy consumption given by the elasticity at mean income is of less relevance here, since the effect at the lower percentiles of the distribution is what matters to more accurately measure any policy response on energy demand. In other words, it is often important to recognise the context dependent variation in the elasticity and to make use of the most applicable elasticity to the policy, in order to achieve a more accurate measurement of its impact on consumption.

Much of the international literature in this area focuses on the mean income elasticities for individual energy goods such as electricity or natural gas - see, for example, Asche et al. (2008), Baker and Blundell (1991) and Bernstein and Madlener (2011). However, there is also a limited body of this literature which has estimated the average income elasticity for total energy expenditure. For example, Meier and Rehdanz (2010) investigated household demand for energy in the UK using panel data over 15 years from 1991-2006 on over 5,000 households, and reported income elasticities ranging from 0.01 to 0.04 depending on the model specification. In examining household energy consumption in Norway for 1993-1995, Nesbakken (1999) estimated the average income elasticity of total household energy demand to be 0.01 and confirmed it to be stable across time. In a subsequent study, Nesbakken (2001) found the average elasticity of total energy demand to be 0.06 for Norwegian households and this represented an average across all heating systems. In general, the income elasticities in the international literature are very small, especially in comparison to those estimated in a number of Irish studies (see below). This is not surprising since the former generally control for the household's stock of energy-using appliances and a change in energy consumption as a result of a change in income can occur indirectly through a change in the stock of appliances.

Most of the Irish literature examining the relationship between energy expenditure and household income make use of the Irish Household Budget Survey (HBS) micro datasets and estimate the constant income elasticity of household demand for energy e.g. Conniffe (2000) considered the 1994-1995 HBS and reported the average income

elasticity for household energy demand to be 0.32. More recently, Eakins (2013) found the average income elasticity of energy demand in the 1999 and 2004-2005 HBS to be 0.25 and 0.24 respectively. Furthermore, he reported that the elasticity is lower at 0.11 and 0.09 when the model controls for a range of other household and dwelling characteristics. Some Irish studies have also included other socio-economic characteristics as explanatory variables in modelling household energy demand, for example Chapter 2 of this thesis.

Thus, within this context, it is clear that the literature concentrates on the average effect of income on household energy consumption rather than the effect across the energy consumption distribution. This chapter aims to fill this gap by examining the variation in the income elasticity of household energy demand across the entire energy expenditure distribution using a micro-econometric analysis of energy expenditure data. To do this, data from Ireland is used, Ireland has both the appropriate micro-data and a history of empirical work in income elasticities upon which this analysis can build. The datasets used are anonymised micro-data files from five waves of a large scale household expenditure survey: the 1987, 1994/1995, 1999/2000, 2004/2005 and 2009/2010 Irish HBS. A two stage instrumental variable quantile regression approach is applied to each cross-section and the pooled observations to estimate elasticities across the distribution of energy expenditure. These elasticities are then compared across high and low energy consumption profiles. In addition, a constant elasticity at the mean is estimated for all samples using a two stage least squares method similar to that used in Conniffe (2000). This sets a benchmark elasticity to which the quantile elasticities can also be compared. The chapter provides evidence that there is significant variation in elasticities across high and low energy consumption contexts and that some interpretative caution should be taken with regard to estimates from constant elasticity models.

The chapter proceeds as follows: Section 4.2 presents a detailed description of the data used in this analysis, while Section 4.3 outlines the two stage instrumental variable quantile regression methodology that is employed. The results of the analysis are presented in Section 4.4, while Section 4.5 concludes with a discussion around the policy implications of this work.

4.2 Data

This chapter uses anonymised micro-data collected in five rounds of the Irish HBS, a survey of a representative random sample of all private households in Ireland which has been carried out periodically since 1951. The main aim of the HBS is to identify

the pattern of household expenditure in order to update the weighting basis of the Consumer Price Index (CPI). The survey involves participant households maintaining a detailed diary of household expenditures over a two week period together with collecting additional information on household facilities and sources of income. The rounds used here are for the years 1987, 1994/95, 1999/2000, 2004/2005 and the most recent 2009/2010 HBS. The analysis is conducted on all five rounds of the HBS and on the pooled sample of all observations across the five HBSs. The 1987 and 1994 HBS are converted to Euro using the fixed exchange rate of 1.27 at the introduction of the Euro and each individual cross-section in the pool is inflated to 2009 prices.

The main variable of interest in the HBS for the purpose of this study is the expenditure under the sub heading fuel and light. While expenditure on fuel and light includes many different energy goods such as candles and firelighters, energy expenditure in this analysis is taken to be any expenditure on electricity, natural gas, oil, coal, turf, anthracite, LPG, paraffin and wood. Another important variable in this study is total household expenditure. It is utilised as a proxy measure of household income and is determined by the aggregate of the expenditures in all ten commodity groups within each HBS. These commodity groups are food, alcoholic drink and tobacco, clothing and footwear, fuel and light, housing, household non-durables, household durables, miscellaneous, transport and other expenditure.

Energy expenditure is the dependent variable in each cross-section. The mean energy expenditure increased from €17.47 in 1987 to €35.12 in 2009, though when adjusted for inflation[2] it was relatively stable across the HBSs, ranging from a low of €31.36 in 1994 to a high of €35.70 in 2004/2005 (see Table 4.1). In each sample, total household expenditure is the independent variable of concern. Inflation adjusted mean total household expenditure increased from €518.27 in 1987 to €904.37 in 2004/2005 and declined to €809.37 in 2009, most likely due to the economic crisis of 2008 and the subsequent impact on consumer spending. Average energy expenditure as a proportion of average total household expenditure decreased over the period from 1987 to 2004/2005 with a slight increase in 2009. This provides some evidence that, post-crisis, household energy increased as a proportion of total household expenditure, which is expected from a good such as energy that is generally considered a necessity. For the pooled cross-section, the mean energy expenditure was €34.30, while the mean total household expenditure was €742.66.

[2]Overall CPI: 1987=55.88, 1994=68.33, 1999=76.18, 2004=93, 2009=100. Housing and Fuel CPI: 1987=51.37, 1994=61.56, 1999=61.83, 2004=83.78, 2009=100. These represent the average monthly CPI across the months the relevant HBS was distributed.

Table 4.1: Mean weekly total expenditure (€'s) and mean weekly energy expenditure (€'s) by sample.

Year	N	Mean Energy Expenditure	Median Energy Expenditure	Mean Total Expenditure	Mean Energy Expenditure as a % of Mean Total Expenditure
1987	7705	17.47	14.58	289.60	6.03%
1994	7877	19.31	17.68	395.85	4.88%
1999	7644	21.25	19.24	601.03	3.54%
2004	6884	29.91	26.96	841.15	3.56%
2009	5890	35.12	31.02	809.37	4.34%
Inflation Adjusted[1]					
1987	7705	34.01	28.38	518.27	6.56%
1994	7877	31.36	28.72	579.31	5.41%
1999	7644	34.38	31.12	788.97	4.36%
2004	6884	35.70	32.18	904.37	3.95%
2009	5890	35.12	31.02	809.37	4.34%
Pooled	36000	34.30	30.60	742.66	4.62%

[1]Overall CPI: 1987=55.88, 1994=68.33, 1999=76.18, 2004=93 and 2009=100. Housing and Fuel CPI: 1987=51.37, 1994=61.56, 1999=61.83, 2004=83.78 and 2009=100. These represent the average monthly CPI across the months the relevant HBS was distributed

The focus of the analysis in this chapter however is on the entire distribution of household energy expenditure, as opposed to the just the averages. Therefore, Table 4.2 presents the deciles of energy expenditure across the individual HBSs and the pooled HBS sample, showing in all samples that energy expenditure is strictly increasing across the deciles. Moreover, Figure 4.1 presents a quantile plot of energy expenditure for the pooled HBS where the trend across the quantiles is much more observable. The quantile plot shows graphically the major quantiles of total household energy expenditure where quantile q is an element of (0, 1) and is defined as that value of energy expenditure that splits the data into the proportions q below and $(1 - q)$ above. The plot indicates that the distribution of energy expenditure is concentrated in the left tail and is thereafter skewed to the right.

Table 4.2: Deciles of weekly energy expenditure (€'s) by sample.

Decile	**1987**	**1994**	**1999**	**2004**	**2009**	**Pooled**
1	4.33	6.01	7.77	10.61	11.87	11.10
2	7.06	9.68	11.35	15.88	17.09	17.03
3	9.44	12.53	14.02	19.73	21.60	21.59
4	11.95	15.19	16.61	23.44	26.33	26.13
5	14.58	17.68	19.24	26.96	31.02	30.60
6	17.34	20.38	21.89	30.92	36.20	35.34
7	20.98	23.74	25.10	35.20	42.04	40.92
8	25.54	27.36	29.23	41.19	49.82	48.21
9	33.26	33.79	36.15	51.31	62.08	60.42

In the analysis dummy variables are also added for the quarters over which the HBS micro-data were collected in order to control for any seasonal changes in energy expenditures across the period taken to complete the survey. In terms of other explanatory variables, the categorical variable *deciles of household gross income* together with *social group* are also used as instruments for total household expenditure. Other socio-economic or household characteristics are not controlled for in this analysis. This is consistent with the previous Irish literature and implies that the estimated income elasticity includes both direct and indirect income effects, where the latter stems from a change in the household's stock of energy using appliances.

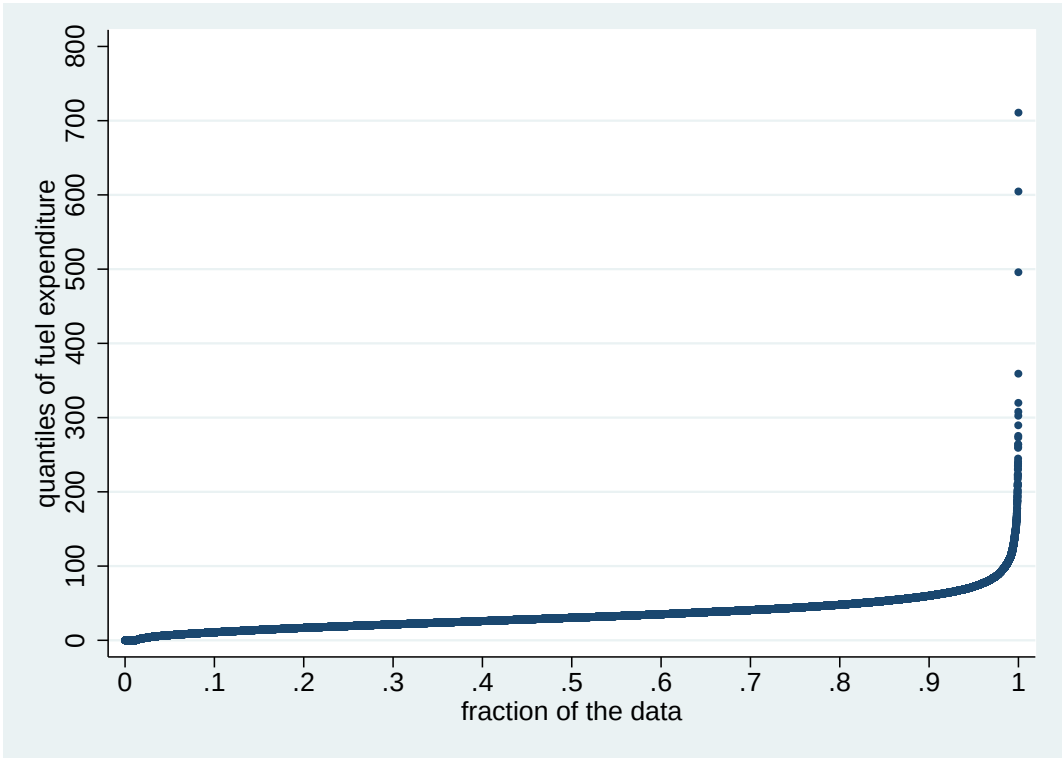

Figure 4.1: Q plot of fuel expenditure for the pooled HBS.

4.3 Methodology

The overall aim of this chapter is to examine the variation in the income elasticities of household energy demand across income deciles for both low and high consumption profiles. To begin, a semi-log model is used of the type specified in most of the previous Irish literature on energy elasticities and also advocated by Prais and Houthakker (1955). They suggest that while a double-log specification is better suited to luxury goods, the semi-log specification is a much better fit for necessity goods. Therefore, the model used here is represented as[3]:

$$X_i = \beta_0 + \beta_1(lnY_i) + \delta Q_t + \epsilon_i \tag{4.1}$$

where the dependent variable X_i denotes the energy expenditure of household i and Y_i is the total household expenditure of household i. Q_t are the quarter time dummies across the period of the HBS under consideration and ϵ_i is the error term. Conniffe (2000) explains that total household expenditure may be a better measure of true long run income for two reasons. Firstly, income tends to fluctuate greatly over shorter

[3]The analysis was also conducted using a linear and double-log specification and the semi-log specification was found to be a better fit.

periods whereas expenditure is more likely determined by average income over the long run. Secondly, there is a tendency in surveys such as the HBS for some participant households to understate their incomes.

In order to set a benchmark, the model is first estimated for each HBS cross-section and the pooled HBS cross-section using an instrumental variable approach similar to that in Conniffe (2000). In order to correct for the endogeneity stemming from the association between fuel expenditure and total expenditure, total household expenditure is instrumented with the categorisation by gross household income decile and by social group in a two stage least squares (2SLS) estimation.

Following this, quantile regressions are also estimated to explore the variability in income elasticities across the distribution of energy consumption. In particular, the p_{th} quantile regression estimators β_0^p, β_1^p and δ^p are chosen to minimize:

$$\begin{aligned} p \sum_{X_i \geq \beta_0^p + \beta_1^p(lnY_i) + \delta^p Q_t} & |X_i - \beta_0^p - \beta_1^p(lnY_i) - \delta^p Q_i| \\ & + (1-p) \sum_{X_i < \beta_0^p + \beta_1^p(lnY_i) + \delta^p Q_t} |X_i - \beta_0^p - \beta_1^p(lnY_i) - \delta^p Q_i| \end{aligned} \tag{4.2}$$

where $0 < p < 1$.

Intuitively, a quantile p can be viewed as the point that minimizes the average weighted distance over the sample where the weights depend on whether the point is above or below the value p. The weight is p for points above the fitted line and $(1-p)$ for points below. For example, in the case of median regression where $p = 0.5$, which is also called least absolute deviations (LAD) regression, β_0^p, β_1^p and δ^p are chosen to minimize:

$$\sum_{i=1}^{n} |X_i - \beta_0 - \beta_1(lnY_i)| \tag{4.3}$$

Here, the weights are equal, so the quantile regression coefficients are estimated by minimizing the absolute deviations from the median and the regression line will pass through a pair of points with half the remaining data points above the line and the other half below the line. The quantile regression methodology is described in detail in Koenker and Bassett (1978) and Koenker and Hallock (2001).

In this analysis, quantile regressions are estimated at each decile for each cross-section and the pooled observations, implying $p = 0.1, 0.2, ..., 0.9$. The coefficients are estimated using a quantile instrumental variable approach to correct for the endogeneity arising from energy expenditure being a direct component of total household expenditure. A similar methodology is outlined in Amemiya (1982) and it involves estimating

a two stage regression identical to 2SLS, though instead the first stage is an ordinary least squares (OLS) regression and the second stage is a quantile regression.

The main parameter of interest is the income elasticity of energy demand, with the elasticity formula for the semi log specification given by β/X. Benchmark elasticities are calculated at the mean energy expenditures (see Table 4.1) and the quantile elasticities are calculated at each decile of energy expenditure (see Table 4.2). Standard errors for the elasticities are obtained using a bootstrap methodology.

4.4 Results

Table 4.3 presents the income elasticities of household energy demand derived from the benchmark 2SLS model and from the two stage quantile models across the five HBS cross-sections and the pooled cross-section. Standard errors are bootstrapped with 500 replications. In terms of the results, the elasticity estimates vary over the period from 1987 to 2009 and they are all highly statistically significant. All the estimated elasticities are between 0 and 1 implying that the demand for household energy increases less than proportionately to income. Thus, household energy is income inelastic, confirming the finding in previous studies that the energy required to light and heat the home is a necessity good.

For the benchmark 2SLS estimates, the elasticity declines from 0.32 in 1987 to 0.28 in 1994/1995. Thereafter, it is steady at 0.25 across 1999 and 2004/05, with a large increase in 2009 to above the 1987 level at 0.33. A declining trend in the income elasticity of household energy demand is not unusual. It is explained by increases in the standard of living where households are equipped with central heating and a basic set of electrical appliances at a minimum. The rise in Ireland's income elasticity of energy demand in 2009 is therefore consistent with a fall in the standard of living following the economic crisis of 2008.

Table 4.3: Estimated income elasticities of household energy demand from the benchmark 2SLS model and the two stage quantile models at each decile.

	1987	**1994/95**	**1999/00**	**2004/05**	**2009/10**	**Pooled**
Benchmark Model						
2SLS	*0.32**	*0.28**	*0.25**	*0.25**	*0.33**	*0.28**
	(0.01)	*(0.01)*	*(0.01)*	*(0.01)*	*(0.02)*	*(0.01)*

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Table 4.3 – continued from previous page

	1987	1994/95	1999/00	2004/05	2009/10	Pooled
Two Stage Quantile Models						
1	0.75*	0.79*	0.57*	0.63*	0.70*	0.69*
	(0.04)	(0.03)	(0.03)	(0.03)	(0.05)	(0.02)
2	0.57*	0.52*	0.42*	0.43*	0.54*	0.49*
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)
3	0.48*	0.42*	0.35*	0.35*	0.46*	0.41*
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
4	0.42*	0.35*	0.32*	0.31*	0.43*	0.36*
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
5	0.35*	0.31*	0.28*	0.28*	0.39*	0.31*
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
6	0.31*	0.27*	0.25*	0.23*	0.36*	0.28*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
7	0.29*	0.23*	0.22*	0.21*	0.32*	0.25*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
8	0.27*	0.20*	0.20*	0.20*	0.29*	0.23*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
9	0.23*	0.16*	0.16*	0.18*	0.23*	0.19*
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)

Bootstrapped standard errors in parenthesis
*significant @ 1% level

The variability of the income elasticity of energy demand across the distribution of energy expenditure is evident in all cross-sections, with the elasticity ranging from 0.16 to 0.79 depending on the decile and cross-section used. This variation is much more conveniently illustrated in the graphs in Figure 4.2. The graphs plot the elasticity points and their 95% confidence intervals for each of the quantile regressions from $p = 0.1$ to $p = 0.9$ over each HBS cross-section. Each graph also shows the 2SLS estimate of the constant elasticity in the continuous black line together with its 95% confidence interval in the dashed line, allowing for a direct comparison to the benchmark elasticity. The 95% confidence intervals shown are based on bootstrapped standard errors with 500 replications.

Comparing the income elasticity estimates across the whole distribution of energy expenditure, which is the main objective of this study, it is apparent that the absolute size of the elasticity is considerably larger for the bottom quantiles and smaller for the top quantiles in each cross-section. The variation in the income elasticity is large with the elasticity likely to decrease as a household moves up the distribution of energy expenditure. As expected, low energy consumption households are much more sensitive to a rise in their incomes relative to high consumption households.

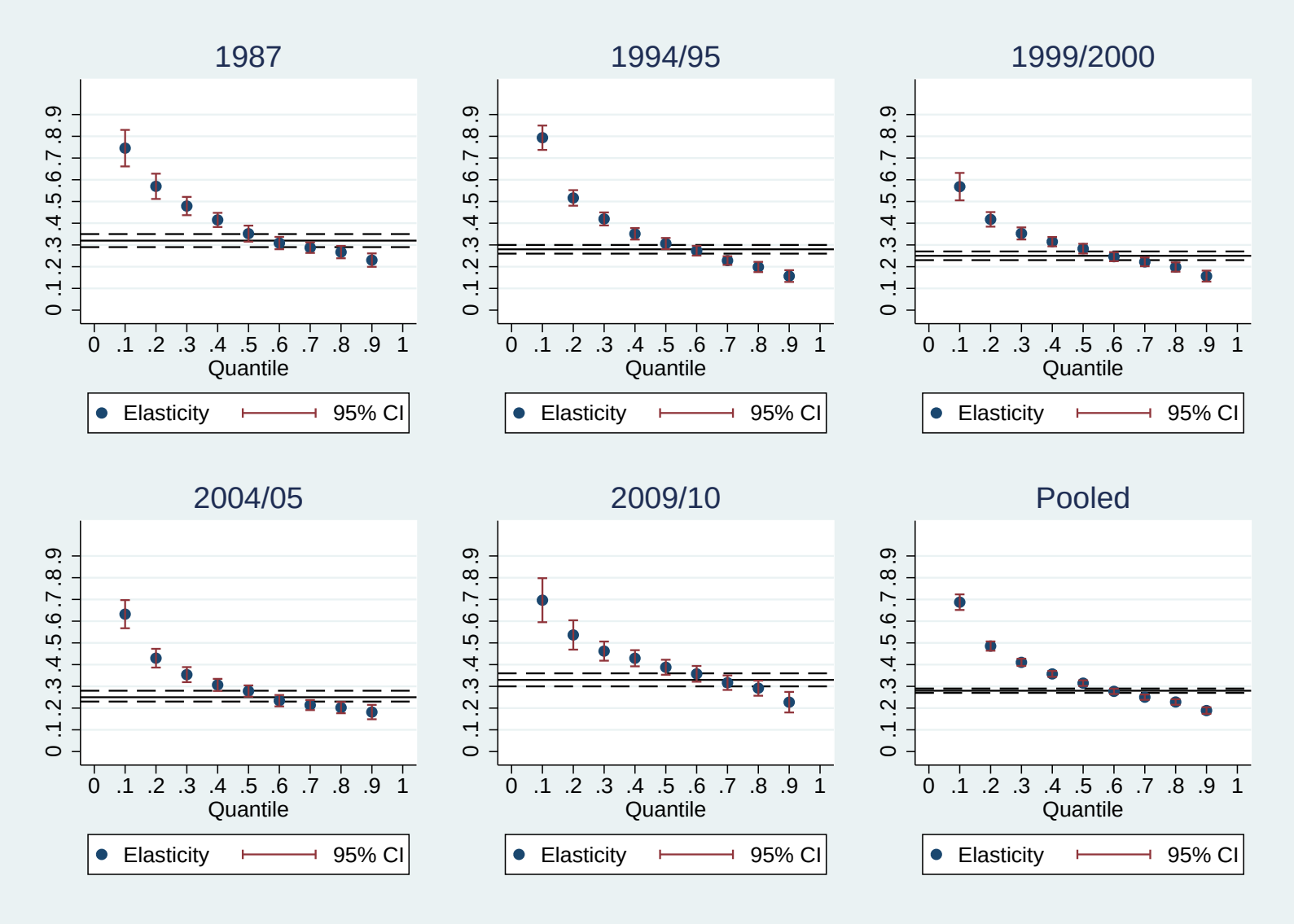

Figure 4.2: Graphs of estimated elasticity points and their 95% confidence intervals.

To help illustrate the implications of this, Table 4.4 outlines a comparison of the estimated pooled elasticities in high and low consumption contexts, where the pooled cross-section results offer an overall view of the variation in the elasticities. In considering the less extreme quantiles, such as the top 40% versus the bottom 40% of the energy expenditure distribution, the percentage difference in the income elasticity is a notable 29%. However, differences become much larger for the more distant quantiles e.g. the percentage difference in the elasticities between the top 10% and the bottom 10% is a very practically significant 263%. Differences are all statistically significant under the F test at the 1% significance level.

Table 4.4: Comparison of the income elasticity of household energy demand in high and low consumption contexts for the pooled cross-section.

Quantiles of Energy Expenditure Distribution		
(1)	**(2)**	**% Difference**
Top 10%	*Bottom 10%*	
0.19	0.69	263%*
Top 20%	*Bottom 20%*	
0.23	0.49	113%*
Top 30%	*Bottom 30%*	
0.25	0.41	64%*
Top 40%	*Bottom 40%*	
0.28	0.36	29%*

*significant @ 1% level

In terms of comparison to the benchmark elasticity, differences are summarized in Table 4.5. With a skewed distribution, the median may become the more appropriate measure of central tendency. Therefore, median regression or LAD can be much more robust in such circumstances. The median (2SLAD) elasticity estimated for the pooled HBS (0.31) is slightly larger than the benchmark constant mean elasticity from the 2SLS estimation (0.28), with a percentage difference of 11%. Also, for the pooled cross-section, the elasticity for the bottom 10% is almost 2.5 times the benchmark elasticity, while in contrast, the benchmark elasticity is about 1.5 times the elasticity for the top

10%. An important implication raised here is that the interpretation of the constant elasticity estimate needs to be treated with care, especially when it is used to advocate a policy which may target the left or right tails of the energy expenditure distribution.

Table 4.5: Comparison of quantile income elasticities of household energy demand to the benchmark for the pooled cross-section.

Benchmark	**Quantiles of Energy Expenditure Distribution**	**% Difference**
2SLS	*2SLAD*	
0.28	0.31	11%*
2SLS	*Bottom 10%*	
0.28	0.69	146%*
2SLS	*Top 10%*	
0.28	0.19	-32%*

*significant @ 1% level

4.5 Conclusion

This chapter used an econometric analysis of the household fuel and light expenditure data from the Irish HBS to examine the variation in the income elasticity of household energy demand across the distribution of energy expenditure. Household energy expenditure, together with some other socio-economic variables including total household expenditure as a proxy for income, are utilised from the 1987, 1994/1995 1999/2000, 2004/2005 and 2009/2010 cross-sections of the HBS to conduct the analysis. A two stage quantile regression approach with bootstrapped standard errors is undertaken to estimate the elasticities at all deciles in the distribution of energy expenditure for each cross-section and their pooled observations. These elasticities are then compared across high and low energy consumption profiles and to a benchmark constant mean elasticity estimated using a similar technique to the two stage least squares method outlined in Conniffe (2000).

The main finding is that there is a large variation in the income elasticity of household energy demand across low and high energy consumption contexts. The absolute

size of the elasticity is considerably larger for the bottom quantiles and smaller for the top quantiles across all cross-sections with a percentage difference of 263% between the top 10% and the bottom 10% in the pooled cross-section. This suggests that households with a low energy expenditure or located in the left tail of the distribution could be up to 3.6 times more responsive to a one percent increase in their income than households with high energy expenditure.

More specifically, there is a distinct difference between the benchmark constant elasticity estimate and the quantile elasticities. The bottom 10% in the pooled data is shown to have a 146% larger elasticity than the benchmark while the top 10% have a 32% smaller elasticity. This provides evidence that households with low energy expenditure are almost 2.5 times more sensitive to a one percent increase in their incomes than the constant mean elasticity would imply. This group is likely to include many households commonly classified as fuel poor.

The benchmark elasticities shown here are broadly consistent with other mean income elasticities in the literature. For example, Pratschke (1969) estimated the income elasticity for household energy demand to be 0.32 for the 1965-1966 HBS. For the 1987 HBS, Conniffe and Scott (1990) found the income elasticity of energy demand to be 0.43, though they applied a method which divided households into different groups and regressed group mean expenditures on group mean incomes. In a separate analysis, Conniffe (2000) considered the 1994-1995 HBS and noted that the income elasticity of energy demand when adjusted for the free electricity allowance is 0.25, an elasticity estimate confirmed by Eakins (2013) for the 1999 HBS also.

Similarly, in considering an alternative methodology and with electricity having the largest share in total household energy consumption, Curtis and Stanley (2016) employed almost ideal demand system (AIDS) models and identified that the income elasticity estimates for electricity vary between 0.29 and 0.84 for Ireland. Furthermore, and in an international context, Madlener and Alt (1996) employed Austrian annual data over the period from 1970 to 1992 and estimated the short run income elasticity of energy demand to be 0.49 in their final model, while the short run income elasticities of residential electricity demand ranged from 0.04 to 3.48 with a mean of 0.28 in a meta-analysis conducted by Espey and Espey (2004). The benchmark total energy elasticity for the pooled model in this study is also an estimated 0.28.

Policymakers recognise household income as one of the main factors influencing the level of fuel poverty, together with fuel prices and the energy efficiency of the housing stock. Policy responses to fuel poverty can include the provision of income support and/or capital improvements to the energy efficiency of dwellings and equipment. The

evidence provided in this chapter suggests that income supports could have a much greater importance for reducing the level of fuel poverty than previous research has suggested and is consistent with the finding that fuel poverty is primarily a matter of inadequate resources as reported by Watson and Maitre (2015). The energy expenditure of households located at the lower end of the energy consumption distribution, where the majority are most likely to be in fuel poverty, are much more sensitive to a rise in their incomes than the constant elasticity at the mean implies. Therefore, such households are benefiting greatly from income supports and such supports should help contribute to lifting them out of fuel poverty. Also, such transfer payments might be advocated given that there could be a 263% difference in the sensitivity of energy expenditure to an increase in income between the bottom 10% and the top 10% in the energy expenditure distribution.

The need to raise residential energy efficiency to advance climate policy goals is also a concern for many policymakers. Some countries subsidise energy efficiency schemes intended to deliver a range of energy efficiency measures for free or at reduced cost to vulnerable households. The results suggest that if energy efficiency measures are installed in low energy consumption households and this reduces the cost of heating such that a household's real income increases, then the household could be more likely to maintain their expenditure on fuel and take the added benefit in additional heat. In other words, the rebound effect is likely to be much higher for low energy consumption households. These results lend support to the findings of both Murray (2013) and Chitnis et al. (2014) that the rebound effects are higher for low income households.

To conclude, allowing for a varying income elasticity of energy demand at different consumption levels shows significant variation compared to the mean elasticity. Policy analyses or forecasting models of residential energy use should take this substantial context dependent variation in the income elasticity into account, particularly where the distributional effects of policy are of interest. Changes in income support measures, energy efficiency supports aimed at vulnerable households or indirect taxation of energy goods will likely produce very different outcomes than the mean elasticities might suggest.

Chapter 5

Consumer Switching in European Energy Markets

5.1 Introduction

A high level of consumer switching can be a desirable attribute of a well-functioning market, as it may be both an indication of the degree of choice available to the consumer and the ability of consumers to exercise this choice. Indeed, consumer switching is understood to play a key role in creating competitive markets, where consumers switch products or services based on differences in prices and quality. Waterson (2003) describes an important paradox of competition, whereby if every consumer thinks the competitive process works well, then it doesn't work. If it is the belief of consumers that the market is functionally competitive and their current supplier offers a competitive price and product, then they don't have any incentive to switch, resulting in unfavourable and sub-competitive outcomes.

It is important to note that the empirical focus in this chapter shifts to being pan-European rather than distinctly on Ireland as in the previous chapters. Since the 1990s the European Union (EU) has put in place legislation for Member States to deregulate and liberalise energy markets with the aim of reducing costs in the energy sector and having the reductions passed onto consumers through lower retail prices. For homogeneous goods such as electricity and natural gas, the main difference across providers is price. Competition is therefore the most important driver of this legislation for the restructuring of energy markets, and thus for it to be successful, it is important that consumers actively engage in switching to help maintain competitive pressure on energy providers. Even when competition is effective for 'active' consumers to some extent, 'passive' consumers may still end up paying higher retail prices for electricity or

natural gas. Furthermore, active consumers do not always switch to the best alternative. Wilson and Waddams Price (2010) show that between 17-32% of electricity consumers who switch purely for price reasons appear to have lost consumer surplus through their choice of a more expensive supplier.

Within this context, it is important for the relevant stakeholders to have an understanding of the factors that influence switching in energy and other markets in order to compare consumer switching across markets and countries. For example, consumers have perhaps the most to gain from switching as a result of lower prices, better quality products and more choice, and so understanding the factors around switching could help them become more informed and engaged in the marketplace. Energy suppliers are required to recognise the motives for consumer switching so that they can tailor prices and services to offer the best alternative and help retain their current consumer base while attracting others. In the context of restructuring of energy markets, policymakers are concerned with increasing competition amongst energy providers. This helps increase consumer welfare and promote further innovation in energy, for example in renewable energy where there is a large drive to achieve carbon abatement and climate change goals. Policymakers also benefit from a greater understanding of the determinants of consumer switching by being able to identify the barriers to consumer switching and, ultimately to competitive markets, so that they can develop more effective and targeted policy measures to intervene in the market and mitigate against such market failures.

In this chapter, the factors influencing consumer switching in Europe are examined using a micro-econometric analysis of consumer switching behaviour data from four independent cross-sections of the European Commission's Consumer Market Monitoring Survey (CMMS); the 2010, 2011, 2012 and 2013 waves. The chapter explores the role of consumers' socio-demographic characteristics, together with their attitudes to the main features of the market, on the propensity to switch product/service or supplier. Pooling the individual waves of the CMMS data creates a complete sample of 674,819 observations, the largest by far of any sample used in empirical studies of consumer switching. The unique nature of the dataset provides information for 27 EU countries across 14 switching markets, namely: bank accounts; loans and credit; investment products; home insurance; vehicle insurance; fixed telephone; mobile telephone; internet; commercial sport; electricity; natural gas; mortgages; life insurance; and, TV subscriptions. For the purpose of this chapter, an overall model for consumer switching is first estimated across all 14 switching markets for the 27 countries and these results are compared to the estimates from separate econometric models for consumer switching for both the

electricity and natural gas markets across the EU27 countries. In an important extension to the analysis, the heterogeneous effects of consumer characteristics and attitudes on switching are also investigated for seven of the EU countries separately. These are: Ireland; United Kingdom (UK); Germany; Denmark; Spain; France; and, Lithuania.

While the chapter aims to provide further evidence for the different impacts on consumer switching for energy markets, it differs from previous work in a number of significant ways. It presents, for the first time, results for two separate energy markets (electricity and natural gas) relative to a number of other different markets, as well as across a large number of different countries. Indeed, it is highly unusual for studies of consumer switching behaviour to have access to such cross-market and cross-country switching data. Moreover, the analysis controls for a greater range of consumer attitudes to the market, including comparability across products, perceived ease of switching, degree of trust in the supplier, and consumer satisfaction in the form of whether they believe the market meets their expectations. Furthermore, unlike previous studies, the consumer switching models presented here also account for whether the consumer has complained about the product/service and to whom they have complained, which allows the switching decision to reflect consumer problems in the market which are severe enough to cause them to complain. Finally, the pooled dataset also includes many consumers that were asked about more than one switching market at the same time, and this provides a suitable opportunity to consider evidence for the impact that switching in other non-energy markets has on switching in energy markets.

The remainder of the chapter proceeds as follows: Section 5.2 presents a review of the related literature, Section 5.3 provides a description of the CMMS data used for the analysis, details of the binary outcome methodology used for estimation are outlined in Section 5.4, results are presented in Section 5.5, and a conclusion follows in Section 5.6.

5.2 Literature

The early literature on consumer switching behaviour focuses primarily on competition from the supplier's side in markets where consumers have costs of switching between competing firms' products or services. For example, Klemperer (1995) surveys the early work and points out that switching costs raise prices and discourage new entry to the market, thus reducing competition. He uses the terms 'switching costs' and 'brand loyalty' interchangeably and suggests from the research surveyed that these factors could also reduce product variety by reducing a supplier's incentives to differentiate

their products from competitors. As a result, he argues that there is a role for public policy to minimize such switching costs. Keaveney (1995) expands on this early research to help understand switching from the consumer's perspective. She collects and analyses a large volume of data on incidents causing consumers to switch services and, using the Critical Incident Technique, she identifies 8 different switching categories that determine consumer switching. The largest switching category was found to be 'core service failures', with 44% of respondents reporting incidents due to mistakes or other technical problems as at least one reason for switching. The next largest category was 'service encounter failures', with 34% reporting incidents around service employee's attitudes as a reason, while the third largest was pricing at 30%. The model in Keaveney (1995) reveals a complex combination of variables involved in a consumer's decision to switch services far beyond just prices or switching costs.

Similarly, Waterson (2003) claims that the assumption that consumers switch in response to price changes alone cannot be made, and that modelling competitive behaviour needs to consider the behaviour of consumers much more closely, rather than solely the behaviour of firms. Indeed, some of the more recent research related to switching behaviour has been in studies from the consumer's standpoint in both the telecommunications (Lyons, 2010; Lopez et al., 2006; Ranganathan et al., 2006) and energy sectors (Giulietti et al., 2005; Ek and Söderholm, 2008; Gärling et al., 2008). For example, for the energy market, Giulietti et al. (2005) distinguishes between the awareness of the opportunity to switch and actual switching in modelling changing gas supplier in the UK. They conclude that although most consumers know they have the opportunity to switch, they find the switching costs too high. The authors also highlight the importance of ease of switching for the consumer. In an econometric study, Ek and Söderholm (2008) examine the determinants of switching or re-negotiating activity amongst Swedish households in the electricity market. Their findings echo those of Giulietti et al. (2005) and also suggest that consumers who perceive relatively high search and information costs are less likely to change electricity supplier, while those with the largest benefits to be gained are more likely to switch or re-negotiate their electricity contract.

In an investigation of the barriers to switching in the retail electricity market in Denmark, Yang (2014) shows that for suppliers, good relationship management is crucial to retaining and attracting consumers. In contrast to other research, little evidence was found for perceived economic benefits having the largest impact on switching, though he points out that this could be a result of the relatively small price differences amongst the electricity retailers considered in the study. He also claims that a solution to tack-

ling the negativity around switching would be to remove the psychological barriers to switching by providing better information and demonstrating the switching process to consumers. In addition, the results from the experiment in Gärling et al. (2008) on a random sample of Swedish consumers in a fictitious electricity market demonstrate that switching increased by removing loyalty, by providing good information on consumption, reducing price and increasing co-operation amongst consumers. Moreover, their results also reveal that providing consumers with the option to choose green electricity had a positive impact on switching.

While there is a broad literature on consumer switching within individual markets, there is a relatively limited body of research that specifically examines factors affecting consumer switching simultaneously across different markets. Gamble et al. (2009) considers consumers' motives for negative attitudes towards switching in the deregulated markets for electricity, landline telecom and home insurance in Sweden using a mail survey of a random sample of 458 household consumers. Their results show that attitudes towards switching supplier in all three markets are related to loyalty to the current supplier, information search costs to compare suppliers and expected economic benefits from switching. Moreover, the authors find that the motives for switching did not differ significantly between the three markets with the exception of expected economic benefits being less important in the home insurance market in comparison to the electricity market. They also reveal that socio-demographic variables had only marginal impacts on switching motives, which did not vary significantly between markets.

In another study to consider differences in factors influencing switching across markets, Waddams Price and Zhu (2016) utilise data from a large scale and nationally representative survey in Great Britain to analyse the process of deciding whether or not to search and switch away from their current supplier in each of eight markets in the previous three years. The markets explored were electricity, mobile phone, fixed phone line rental, national and overseas (fixed line) calls, broadband internet, car insurance, mortgage and current bank account. In contrast to Gamble et al. (2009), their results show significant differences between markets with consumers less likely to search/switch their fixed phone line and their mortgage providers than they are to search/switch their electricity supplier. Furthermore, they find that young and old consumers were more active in switching, while income and gender also matter, with males being less likely to switch in the analysis. Interestingly, they discover that past switching experience also has an effect on the probability of switching in some markets with the greatest impacts evident in the fixed phone line, car insurance and mortgage markets. Finally, the authors note that higher switching in one service is associated

with switching in other services, with the possibility that experience itself could affect switching activity, rather than some respondents being inherently more prone to active consumerism. Most recently for the electricity market in the UK, He and Reiner (2017) also identify differences in the probability of switching among groups with different experiences of switching, where the likelihood of switching electricity supplier increases with experience of switching in other markets.

Overall, in the context of this previous literature, this chapter contributes to the research on consumer switching in several important ways. First, it econometrically examines consumer switching using a unique pooled dataset that captures a very large sample of consumers' reported switching behaviour, together with their socio-demographic characteristics and a rich array of their attitudes to the main features of the market. This is unusual for studies of consumer switching behaviour. Second, it examines the factors related to switching in the two energy markets separately, and then for comparison, investigates factors affecting consumer switching across the 14 switching markets combined. Third, it is the first study of its kind to analyse consumer switching behaviour across a large number of countries, with the analysis comprising switching in all EU27 countries. Fourth, it offers greater insight into the influence of switching in other markets on switching in energy markets, because of the nature of the survey whereby many consumers were asked about more than one switching market simultaneously.

5.3 Data

This chapter uses micro-data collected in four waves of the CMMS. The survey was undertaken in a consistent format on an annual basis from 2010-2013 for the Directorate for Consumer Affairs and the Executive Agency for Health and Consumers of the European Commission to provide essential information for the Consumer Markets Scoreboard. Functional consumer markets are of great importance to achieving the overall objectives of the EU and the Scoreboard is primarily used to determine which markets are failing to deliver the desired outcomes for consumers who have had recent purchasing experience in these markets. The CMMS monitored over 50 consumer markets, including the electricity and natural gas markets, in the four waves from 2010-2013 using an annual telephone survey on a representative sample of individual consumers for each market in the 27 EU Member States, together with Norway (in the 2010, 2012 and 2013 wave), Iceland (in the 2012 and 2013 wave) and Croatia as a member of the 28 EU Member States in the 2013 wave.

At the beginning of each telephone survey the respondent was screened for the markets in which they had made a purchase or payment. A maximum of 50 markets were screened per respondent, though from the moment it was established that the respondent had experience in eight markets, the actual interview for each of these eight markets commenced. If the respondent was found to have experience in fewer than eight out of fifty markets, the survey interview was undertaken for each of the markets he/she had experience in. The markets were screened in an order taking into account the incidence rate of each market with markets that have a low incidence rate being screened first. The sample size for each market was set at 500 individuals per country for all countries except for Malta, Cyprus and Luxembourg, where the sample size was set at 250. The main aim of the survey is to evaluate consumer experiences in five key market components, namely: comparability; trust; the extent to which the market lives up to expectation; complaints; and, consumer switching.

For the purpose of this study, the analysis is conducted on a pooled cross-section of all consumers in the four waves. The consumer markets examined are limited to the 14 so-called 'switching markets' across the different waves, and consist of the 11 switching markets (including the electricity and natural gas markets) surveyed in 2010, as well as the mortgages, private life insurance, and TV subscription markets introduced to the survey in 2011. The analysis is also restricted to consumers in the 27 EU Member States as these were the countries included in all four waves. Upon preliminary data checking, 875 observations were dropped from the overall analysis because of duplication and, consequently, complete data is available for 674,819 observations. While these duplicated observations were for the Netherlands in the 2010 wave, consumers from the Netherlands still represent around 4% of the sample, equal to the other countries in terms of representation. Furthermore, unique Personal Identification Numbers (PINs) were missing in the 2010 wave for 3,439 and 2,072 observations from Belgium and Luxembourg respectively. These observations were dropped from the analysis of a sub-sample of energy consumers who were surveyed on three or more switching markets and depended on the PINs to determine whether or not they had switched in other non-energy markets. There was no apparent reason for the duplication of the data or the missing PINs. Complete data is available for 45,026 observations in the electricity market and for 43,241 observations in the natural gas market.

The dependent variable used in this study is derived from responses in the survey to reported switching behaviour in the different switching markets. The variable is binary and is described in Table 5.1. Within the 14 switching markets, fewer than 15% of consumers have switched product/service or supplier with the vast majority

of consumers choosing not to switch in any of these markets. Figure 5.1 illustrates the proportion of consumer switching across the 14 switching markets in the sample. The home insurance market has the lowest proportion of switching at 9.26%, while the mobile telephone market has the highest proportion of switching at 23.49%. The gas and electricity markets have a relatively low proportion of switching when compared to the other markets at 9.42% and 10.53% respectively. The proportion of consumer switching across the EU27 countries is represented in Figure 5.2. The proportion of consumer switching is lowest in Luxembourg at 6.58% and highest in Lithuania at 21.73%.

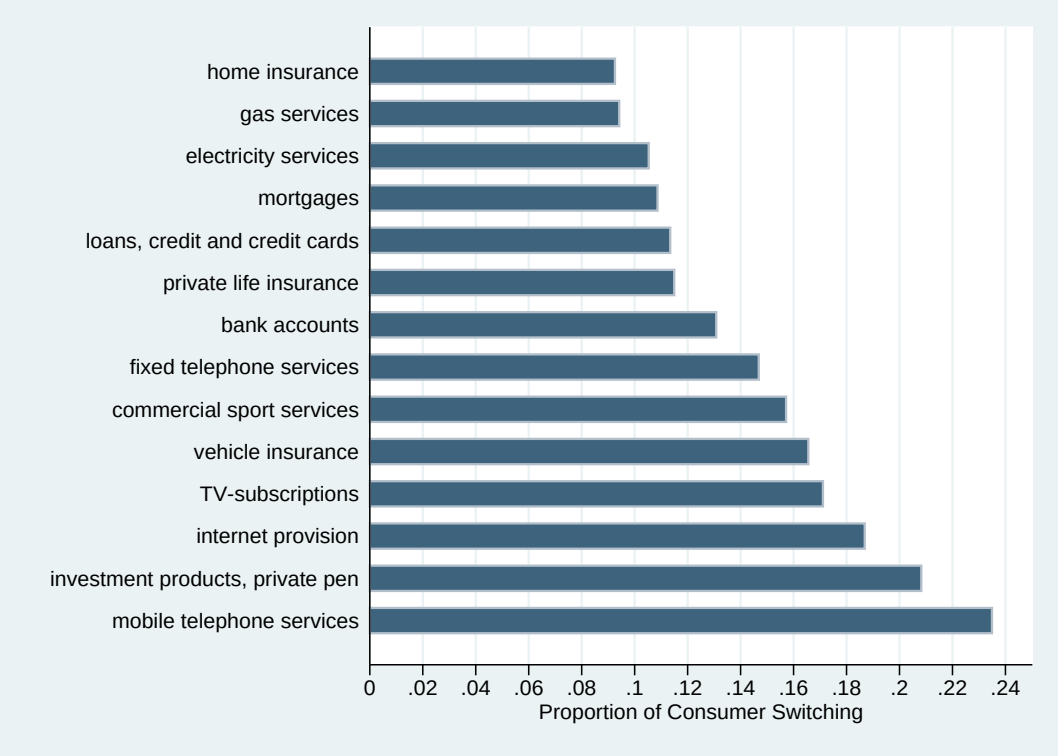

Figure 5.1: Proportion of consumer switching by market.

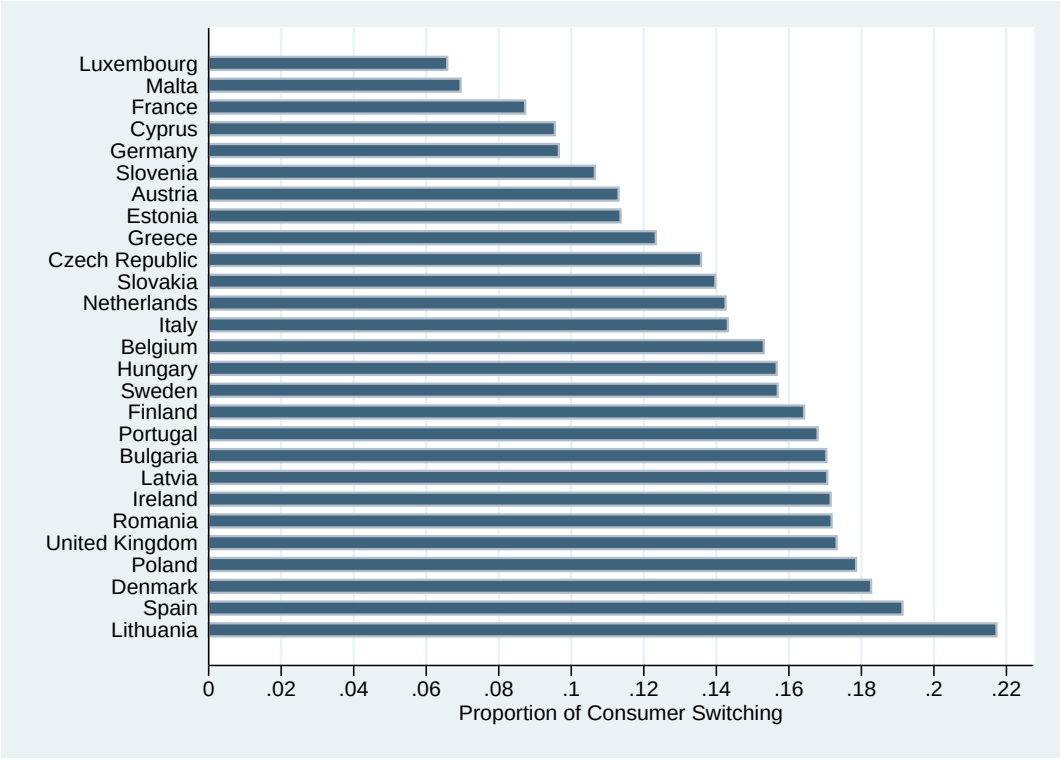

Figure 5.2: Proportion of consumer switching by EU27 country.

In terms of the independent variables, socio-demographic data was collected as part of the CMMS for each consumer in all four waves and included: gender; age; occupation; and, education. The sample descriptive statistics for these variables are presented in Table 5.1. In each CMMS wave the consumer's rating of the market components of 'comparability', 'trust', 'ease of switching' and 'lives up to expectation' was also gathered and based on a scale from 0 to 10, with the number between 0 and 10 indicating the strength of the consumer's attitude or opinion. In this analysis, categorical variables are derived for each of these market components by sub-dividing the scale 0 to 10 into five categories as described for each distinct component in Table 5.1. These four market components together with the 'complaints' aspect of the survey are assumed to capture the main characteristics of each consumer market. 'Comparability' demonstrates the level of difficulty for a consumer to compare goods or services in a market and indirectly includes a price and quality comparison. 'Trust' is a measure of the consumer's confidence in the supplier's capacity to respect the rules and regulations that are in place in the market to protect the consumer. 'Ease of switching' is a gauge of the perceived effort in switching for both consumers who have actually switched and for consumers who have not. The 'lives up to expectation' element measures consumer satisfaction in whether or not the market generally lives up to the consumer requirements. Finally,

'complaints' reflects the severity of a problem impacting on consumers and is seen as a sign of an underperforming market. For the 'complaints' component, four different categories are created to indicate to whom the individual consumer had complained (see Table 5.1).

The sample descriptive statistics for the two energy markets, electricity and natural gas, as well as the descriptive statistics for a sub-sample of 43,648 observations for energy consumers who were surveyed on three or more switching markets in the CMMS are also presented in Table 5.1. In addition to the variables above, the binary variable 'other non-energy switches' is also controlled for in the sub-sample analysis. This variable indicates if a consumer has made a switch in at least one other market that they were asked about in the CMMS, outside both the electricity and natural gas markets, and is derived using the PIN of the consumer. Table 5.1 shows that the proportion of the sub-sample with no other non-energy market switches is 75%, while the proportion with at least one other switch in a non-energy market surveyed is 25%.

Table 5.1: Variable definitions and sample descriptive statistics.

Variable Name	Variable Description	Electricity %	Natural Gas %	All 14 Markets %	Energy Markets† %
Dependent Variable					
Consumer switch	=1 if individual switched; =0 if didn't switch	10.53%	9.42%	14.69%	9.54%
Independent Variables					
Individual characteristics:					
Female	=1 if individual is female; =0 if male	56.99%	59.42%	56.39%	57.69%
Age	18-34 years	19.83%	17.87%	21.74%	16.78%
	35-54 years	40.05%	38.65%	43.23%	39.75%
	55+ years	40.12%	43.47%	35.03%	43.47%
Occupation	Self-employed	7.25%	6.68%	8.18%	6.82%
	Manager	5.28%	4.69%	6.13%	4.90%
	White collar	26.96%	26.86%	30.07%	26.95%
	Blue collar	14.50%	13.07%	14.67%	13.96%
	Student	3.68%	3.70%	4.48%	3.02%
	House-person	7.44%	6.95%	6.91%	6.86%
	Unemployed	7.02%	6.90%	6.23%	6.63%
	Retired	27.87%	31.15%	23.33%	30.87%
Education	<15 years	20.75%	19.99%	17.46%	20.61%
	16-19 years	33.09%	33.18%	32.55%	33.84%
	20+ years	42.36%	42.97%	45.33%	42.44%
	Still studying	3.80%	3.87%	4.65%	3.10%

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Table 5.1 – continued from previous page

Variable Name	Variable Description	Electricity %	Natural Gas %	All 14 Markets %	Energy Markets† %
Communication characteristics:					
Phone	Fixed line only	6.24%	6.58%	3.83%	5.79%
	Mobile only	32.82%	27.80%	26.89%	27.36%
	Mixed	60.94%	65.62%	69.28%	66.85%
Internet usage	=1 if access to internet; =0 if no access to internet	71.69%	69.32%	79.52%	70.97%
Year	2010	24.89%	25.40%	21.12%	20.45%
	2011	24.00%	23.82%	25.98%	22.03%
	2012	24.47%	25.42%	26.39%	27.55%
	2013	26.64%	25.36%	26.51%	29.98%
Market indicators:					
Comparability	Very difficult	12.10%	9.11%	5.75%	10.31%
	Difficult	8.70%	6.40%	6.73%	7.34%
	Neither difficult or easy	28.83%	29.82%	29.20%	29.49%
	Easy	21.72%	21.57%	27.48%	21.33%
	Very easy	28.65%	33.10%	30.85%	31.54%
Trust	Strong mistrust	8.71%	6.27%	5.82%	7.27%
	Mistrust	8.65%	6.56%	7.20%	7.34%
	Neither mistrust or trust	30.66%	30.55%	31.31%	30.50%
	Trust	28.42%	29.32%	31.98%	28.81%
	Strong trust	23.56%	27.30%	23.69%	26.08%

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Table 5.1 – continued from previous page

Variable Name	Variable Description	Electricity %	Natural Gas %	All 14 Markets %	Energy Markets† %
Ease of switching	Very difficult	16.01%	14.68%	7.47%	15.05%
	Difficult	6.35%	6.36%	6.03%	6.22%
	Neither difficult or easy	29.62%	30.83%	28.32%	29.53%
	Easy	22.51%	21.94%	25.25%	22.33%
	Very easy	25.50%	26.19%	32.93%	26.87%
Lives up to expectation	Very poor	5.37%	4.05%	3.37%	4.56%
	Poor	4.15%	3.40%	3.59%	3.64%
	Neither poor or well	24.03%	24.34%	25.10%	24.12%
	Well	30.43%	30.55%	34.79%	30.26%
	Very well	36.02%	37.66%	33.16%	37.43%
Complaints	None	90.57%	93.72%	89.26%	92.97%
	To a retailer/provider	4.90%	3.48%	5.97%	3.79%
	To an official third party	0.44%	0.33%	0.55%	0.31%
	To friends/family	4.08%	2.46%	4.22%	2.93%
Other non-energy switches	None				75.03%
	At least one other switch				24.97%
Observations		45,026	43,241	674,819	43,648

† Sub-sample of energy consumers surveyed on three or more switching markets

5.4 Methodology

The decision by consumer i to switch product/service or supplier in market m (S_{im}) is modelled as a function of a vector of socio-demographic and socio-economic variables (X_i) and a vector of consumer rated market components (A_{im}) relating to the main characteristics of a consumer market, such that:

$$S_{im} = f(X_i, A_{im}, Y_i, M_m, C_i, \epsilon_{im}) \tag{5.1}$$

S_{im} is an indicator variable taking a value of one if the consumer switches product/service or supplier and a value of zero otherwise. The variables included in X_i are the individual characteristics of each consumer and include gender, age category, occupation category and the category of years spent in education. X_i also includes variables describing the communication features available to the consumer. These are: a categorical variable for the type of phone device used by the consumer (i.e. fixed line only, mobile only or mixed), as well as an indicator variable for whether the consumer has access to the internet for private reasons. The variables included in A_{im} include categorical variables for the consumer rated responses to the market components of comparability, trust, ease of switching and the extent to which the market lives up to expectation, as well as a categorical variable indicating to whom a consumer made a complaint, if any. The function also includes fixed effects for the CMMS wave year (Y_i), market type (M_m) and country (C_i). ϵ_{im} is a stochastic error term.

A binary logit model is estimated to account for the binary nature of the dependent variable, and the model defines $P_i = P(S_{im} = 1)$ as the probability that consumer i switches product/service or supplier. Under the assumptions of the logit model $P_i = \Lambda(\boldsymbol{X}'\beta)$, where $\Lambda(.)$ represents the logistic cumulative distribution function (i.e. $\Lambda(\boldsymbol{X}'\beta) = \frac{e^{\boldsymbol{X}'\beta}}{1+e^{\boldsymbol{X}'\beta}}$), β is a vector of parameters and the vector $\boldsymbol{X}$ includes X_i, A_{im}, Y_i, M_m and C_i. Estimation provides $\hat{\beta}$, unbiased estimates of the model coefficients β and it can easily be shown that $\ln(\frac{P}{(1-P)}) = logit(P) = \boldsymbol{X}'\beta$, which implies that the estimated odds ratio of switching product/service or supplier $\frac{P}{(1-P)}$, is equal to $\exp(\boldsymbol{X}'\beta)$.

In allowing for the multilevel nature of the data where there is a natural classification to the observations at a market level within a country, the model is estimated using cluster robust standard errors at the market and country level. In addition, the model is weighted by the population of each country in the EU27 so that the estimation reflects the total number of consumers with purchasing experience in the EU27.

As well as the overall main model examining the factors associated with switching

across all markets in all countries, separate models are estimated for both the electricity and natural gas markets to examine the various heterogeneous impacts on switching in the energy markets compared to the overall main model. Moreover, to consider whether switching in other non-energy markets influences switching in the energy markets, an additional model is estimated on a sub-sample of observations for energy consumers (both electricity and gas) who were asked about at least three switching markets in the CMMS. A binary variable Z_{im} representing whether or not consumer i in energy market m has switched in at least one other non-energy market is added to the function for S_{im}, such that:

$$S_{im} = f(X_i, A_{im}, Y_i, M_m, C_i, Z_{im}, \epsilon_{im}) \tag{5.2}$$

The indicator variable 'other non-energy switches' acts as a proxy for the underlying propensity to switch for an individual consumer, with a higher propensity captured through their choice to switch in other-non energy markets they were surveyed on. This should help determine whether certain individuals with a higher underlying propensity to switch are more inclined to switch in the energy markets, while others may be more affected by consumer inertia.

In an important extension to the analysis, and to compare the heterogeneous effects of the socio-demographic factors and the consumer rated market components on consumer switching across countries, separate models are also estimated for each of seven different EU27 countries, namely: Ireland, United Kingdom (UK); Germany; Denmark; Spain; France; and, Lithuania.

Table 5.2 presents the hypothesised direction of effects for the potential factors influencing consumer switching. It is anticipated that consumer's age will play a role in the propensity to switch, with the expectation that younger consumers will be more likely to switch and older consumers will be less likely to switch. Older consumers tend to be more risk averse and have fixed incomes, thus their odds of switching are expected to be lower. For example, Burnett (2014) established that individuals over 75 are less likely to switch household communication services in the UK. Interestingly, however, some more recent studies of switching in energy markets have shown the opposite effect, and found that older consumers are more active in switching (Waddams Price and Zhu, 2016; Pomp et al., 2005). It is also expected that more years spent in education will be associated with a positive effect on the propensity to switch. Hausman and Sidak (2004) argued that the higher switching costs for less educated consumers due to a lack of information about switching opportunities can lead to imperfectly competitive markets with higher prices.

In relation to the communication features available to individuals, the anticipation

Table 5.2: Hypothesised direction of effects on the propensity to switch.

	Direction
Individual Characteristics	
Female	?
Young individuals	+
Old individuals	-
Occupation	?
Education	+
Own a mobile phone	+
No internet access	-
Market Indicators	
Comparability	+
Trust	-
Ease of switching	+
Lives up to expectation	-
Complaints	+
Other non-energy switches	+

is that mobile phone ownership will be associated with a greater likelihood of switching especially because of the smart capabilities of many mobile devices. Indeed, utilising a survey for Ireland on a sample of fixed-line broadband, mobile and telephony customers, Lunn and Lyons (2017) established that respondents with smartphones had stronger switching intentions. Access to the internet is generally assumed to reduce consumer search costs by making comparability amongst products and suppliers more efficient, thus no internet access is expected to be associated with a lower likelihood of switching. In controlling for gender and occupation, there are no a priori expectations.

In terms of market indicators, it is hypothesised that higher comparability in the marketplace will make consumers more likely to switch, with the ease of comparison related to lower searching costs. It is also expected that strong trust in the supplier, and a market living very well up to consumers' expectations will be associated with consumers being less likely to switch. This is based on evidence from previous studies which suggest that trust, together with satisfaction, are strong predictors of a consumer's commitment and loyalty to service providers (Sharma and Patterson, 2000). In addition, it is anticipated that consumers with complaints, which reflect the severity of the problems they have in the marketplace, will be much more likely to switch. Finally in relation to other non-energy switches, and established on previous evidence

provided by Giulietti et al. (2005) and Waddams Price and Zhu (2016), it is hypothesized that switching in other non-energy markets will have a strong positive influence on the likelihood of switching in energy markets.

5.5 Results

5.5.1 Switching in all markets

Table 5.3 presents the results from the overall binary choice logit model of consumer switching. The table presents estimated odds ratios on the decision to switch product/service or supplier from three models. The standard errors are reported in Appendix C, Table C.1. The first model includes the consumers' socio-demographic characteristics along with CMMS wave fixed effects, the second model adds market and country fixed effects, and finally, the third (and main) model also controls for the consumer rated market components. An examination of the estimated odds ratios across all three models highlights the requirement for the inclusion of market and country fixed effects, as well as the robustness of the findings in the second and third models to the inclusion of the consumer rated market characteristics. The final model has a Wald Chi-square test statistic of 12,193, up from 2,425 in model (2), which suggests that the variables controlled for here result in a large improvement in the fit of the model.

Table 5.3: Consumer switching logit results (odds ratios) weighted by EU27 population.

VARIABLES	(1) Consumer Switch	(2) Consumer Switch	(3) Consumer Switch
Female	0.953**	0.945***	0.986
Age			
18-34 years	1.120***	1.110***	1.122***
35-54 years	*Ref*	*Ref*	*Ref*
55+ years	0.923***	0.909***	0.916***
Occupation			
Self-employed	1.269***	1.151***	1.080***
Manager	1.143***	1.119***	1.105***
White collar	*Ref*	*Ref*	*Ref*
Blue collar	1.056	0.931***	0.932***
Student	0.981	0.935	0.959
House-person	0.958	0.856***	0.864***
Unemployed	1.242***	1.008	0.952

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Table 5.3 – continued from previous page

VARIABLES	(1) Consumer Switch	(2) Consumer Switch	(3) Consumer Switch
Retired	0.989	0.886***	0.912***
Education			
<15 years	1.127**	0.999	0.978
16-19 years	1.008	0.993	0.981
20+ years	*Ref*	*Ref*	*Ref*
Still studying	1.078	1.007	1.005
Phone			
Fixed line only	0.812***	0.904*	0.928
Mobile only	1.124**	0.989	0.987
Mixed	*Ref*	*Ref*	*Ref*
Internet			
Internet usage	*Ref*	*Ref*	*Ref*
No internet usage	0.695***	0.669***	0.707***
Year			
2010	*Ref*	*Ref*	*Ref*
2011	0.951	1.005	0.997
2012	0.794***	0.856**	0.886***
2013	0.792***	0.856**	0.891**
Market			
Electricity		*Ref*	*Ref*
Bank accounts		1.121	0.967
Loans and credit		0.975	0.961
Investment products		1.724***	1.650***
Home insurance		0.817	0.825
Vehicle insurance		1.420*	1.408*
Fixed telephone		1.487**	1.393*
Mobile telephone		2.175***	1.825***
Internet		1.596**	1.339*
Commercial sport		1.095	1.147
Gas		0.903	0.962
Mortgages		0.815	0.881
Private life insurance		0.865	0.915
TV subscriptions		1.335	1.151
Country			
Germany		*Ref*	*Ref*
Austria		1.288*	1.135
Belgium		1.859***	1.786***
Bulgaria		2.199***	1.803***

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Table 5.3 – continued from previous page

VARIABLES	(1) Consumer Switch	(2) Consumer Switch	(3) Consumer Switch
Cyprus		1.066	1.009
Czech Republic		1.640***	1.479***
Ireland		2.099***	1.812***
Denmark		2.299***	2.222***
Estonia		1.317*	1.324*
Greece		1.452***	1.370**
Spain		2.516***	1.872***
Finland		1.992***	1.868***
France		0.929	0.983
Hungary		2.073***	1.778***
Italy		1.843***	1.633***
Lithuania		2.651***	2.286***
Luxembourg		0.674***	0.718***
Latvia		2.089***	2.070***
Malta		0.815*	0.834*
Netherlands		1.696***	1.661***
Poland		2.226***	1.890***
Portugal		2.028***	1.686***
Romania		2.214***	1.820***
Sweden		1.870***	1.696***
Slovenia		1.306*	1.204*
Slovakia		1.677***	1.486***
United Kingdom		2.159***	1.992***
Comparability			
Very difficult			1.138**
Difficult			1.316***
Neither difficult or easy			1.139***
Easy			1.063**
Very easy			*Ref*
Trust			
Strong mistrust			2.162***
Mistrust			2.063***
Neither mistrust or trust			1.764***
Trust			1.348***
Strong trust			*Ref*
Ease of switching			
Very difficult			0.301***
Difficult			0.360***
Neither difficult or easy			0.375***
Easy			0.593***
Very easy			*Ref*

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Table 5.3 – continued from previous page

VARIABLES	(1) Consumer Switch	(2) Consumer Switch	(3) Consumer Switch
Lives up to expectation			
Very poor			1.175***
Poor			1.449***
Neither poor or well			1.250***
Well			1.129***
Very well			*Ref*
Complaints			
None			*Ref*
To a retailer/provider			3.341***
To an official third party			4.604***
To friend/family			3.296***
Constant	0.186***	0.098***	0.082***
Observations	674,819	674,819	674,819
Wald χ^2 Statistic	589.27	2,424.70	12,192.52
		***p<0.01, **p<0.05, *p<0.1	

Overall, the results of the main model show that consumer attitudes to the main characteristics of the market are very important factors in explaining whether or not they switch product or supplier in the 14 switching markets. Piccione and Spiegler (2012) report that when consumers have limited comparability, firms can make profits in line with a market that is not fully competitive. Surprisingly however, the results here indicate that consumers who perceive it much more difficult to compare products and services in the market are more likely to switch compared to consumers who perceive it to be very easy. This could be because consumers who find it very easy to compare products/services could have switched in years prior to being surveyed or are consuming their optimal choice within the market and have no inclination to switch again, whereas consumers that view it difficult to compare products/services may be uncertain of their current product or supplier and thus be inclined to switch. Unfortunately, the CMMS data does not include information on past switching beyond the timeframe of the survey and so the analysis was unable to control for this effect. Another possible explanation could be that individuals only switch after searching, and searching leads you to discover whether comparability is high or low. It is important to note that consumers in the survey were asked for their perception of comparability whether they did or didn't switch. If the general perception of non-searchers is that comparability is easy when

searchers have learned that comparability is actually difficult, then the fact that some searchers will have switched helps to explain the finding that consumers are more likely to switch when they perceive comparability to be difficult. It would be helpful for the analysis to know if the consumers who didn't switch had even considered switching or whether they had engaged in any search activities.

Relative to consumers with a strong trust in their supplier's capacity to respect the rules and regulations in place to protect them, consumers with a higher level of mistrust in their suppliers or providers are more likely to switch. Indeed, a consumer has odds of switching if he/she has mistrust or strong mistrust in the supplier that are over double the odds of a consumer with strong trust. This provides strong evidence that trust inspires loyalty to a supplier and is a factor influencing the consumer's decision to switch. Similarly, a consumer's perceived difficulty in the ease of switching is found to be another significant characteristic of the market determining whether or not a consumer switches. In fact, consumers are associated with odds of switching that are two thirds less when the ease of switching is recognised as being more difficult rather than very easy in a market. The ease of switching identifies with the perceived costs and barriers to switching. For example, consumers could observe switching as a complex process involving time and money for which there may be no guarantee that their decision to switch is the right one. These results are consistent with the findings in the previous literature exploring switching costs (Giulietti et al., 2005).

In controlling for consumer's satisfaction with the product/service in this analysis, the results demonstrate that the consumer's perception of whether the market lives up to expectation matters for their decision to switch. Consumers are found to be considerably more likely to switch when they observe the market as 'poor' in living up to their expectation compared to it living 'very well' up to expectation. This reaffirms the results from Sharma and Patterson (2000) which demonstrate that satisfaction together with trust are strong predictors of loyalty. Moreover, the odds of switching for consumers who made a complaint to an official third party are found to be 4.6 times larger than the odds for those consumers who didn't complain. Consumers are also shown to have higher odds of switching if they have complained to friends or family about the market in comparison to consumers who didn't complain, equivalent to the likelihood of switching if they made a complaint to the retailer or provider directly. This evidence suggests that if consumers are impacted enough by problems in the market to just complain to friends or family, then this still contributes greatly to their choice to take action and switch product or supplier.

In terms of the socio-demographic variables, the consumer's gender or the number

of years spent in education are estimated to have no significant effects on consumer switching. On the other hand, the consumer's age and occupation are found to have statistically significant impacts on switching across the 14 markets. Consumers aged between 18 and 34 years old are statistically more likely to switch than consumers in the reference age category 35-54 years, while consumers aged 55 or older are less likely to switch relative to the reference category. For occupation, consumers who are self-employed or managers are predicted to have a higher likelihood of switching compared to consumers with white collar occupations, whereas consumers with blue collar occupations, or who are house-persons or retired, are predicted to have a lower likelihood of switching in comparison to white collar workers. Findings in Lunn and Lyons (2017) suggest an interaction effect between age and employment status with working individuals in Ireland who are over 55 being more likely to switch broadband product or service provider than their retired counterparts, though the evidence here contradicts this finding.

Furthermore, in considering the effects of the communication features available to consumers on switching, the results reveal that the type of phone device, whether fixed or mobile, used by the consumer is not a significant influence in the decision to switch products or supplier across the markets, However, a consumer's accessibility to the internet for private reasons is revealed to be a very significant factor in their switching behaviour. Specifically, the odds of switching are almost a third less for consumers with no access to the internet for private reasons than consumers with access to the internet. This may suggest that consumers use the internet as an instrument to compare the quality and price of different products and suppliers within a market, helping to lower switching costs and thus aid their decision to switch.

It is worth highlighting the estimated differences in consumer switching behaviour across the 14 markets compared to the electricity market which is reserved as the baseline market. The results show that relative to consumers in the electricity market in the EU27, consumers in the investment products and mobile telephone markets are much more likely to switch products or suppliers, with both differences statistically significant at the 1% level. In the vehicle insurance, fixed telephone and internet markets, consumers are also found to be more inclined to switch than in the electricity market, though the differences are only statistically significant at the 10% level. There are no significant differences in consumer switching between the two energy markets, electricity and natural gas. For differences in consumer switching across countries, it is notable that consumers in most EU27 countries are more inclined to switch products or suppliers in comparison to consumers in Germany, with consumers in Lithuania and

Denmark having odds of switching over 2.2 times larger than the odds of switching for consumers in Germany. Consumers in Ireland, Spain and the UK are all found to have higher odds of switching, while consumers in Austria and France are statistically just as likely to switch products/suppliers as consumers in Germany.

5.5.2 Switching in energy markets

To examine the heterogeneous impacts on switching in the energy markets, separate models are also presented for both the electricity and natural gas markets. The results from these energy market models are displayed in Table 5.4, while the standard errors are reported in Appendix C, Table C.2. It is of particular note that, unlike in the previous models, the socio-demographic and socio-economic characteristics of the consumers are found to have no significant role in the propensity to switch in the electricity and natural gas markets. This is in line with previous studies on switching in energy markets e.g. Pomp et al. (2005). Consumers in both energy markets are less inclined to switch products or suppliers if they have no internet usage relative to consumers with internet usage. This result is in agreement with the general view that internet access reduces consumer search costs to such an extent that markets become more competitive.

Table 5.4: Consumer switching logit results (odds ratios) across energy markets and weighted by EU27 population.

VARIABLES	Electricity Consumer Switch	Natural Gas Consumer Switch	Energy Markets† Consumer Switch
Female	0.969	1.025	0.977
Age			
18-34 years	1.006	0.953	1.028
35-54 years	*Ref*	*Ref*	*Ref*
55+ years	0.989	0.991	0.950
Occupation			
Self-employed	1.043	1.041	0.906
Manager	0.836	1.016	1.030
White collar	*Ref*	*Ref*	*Ref*
Blue collar	0.938	0.918	0.872**
Student	0.697*	0.892	0.613
House-person	0.934	0.823	0.819
Unemployed	0.984	0.930	1.009
Retired	0.961	0.898	1.028

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Table 5.4 – continued from previous page

VARIABLES	Electricity Consumer Switch	Natural Gas Consumer Switch	Energy Markets† Consumer Switch
Education			
<15 years	0.991	1.026	1.037
16-19 years	1.011	0.986	1.040
20+ years	*Ref*	*Ref*	*Ref*
Still studying	1.006	0.935	1.253
Phone			
Fixed line only	0.781*	1.018	1.001
Mobile only	0.918	1.032	0.942
Mixed	*Ref*	*Ref*	*Ref*
Internet			
Internet usage	*Ref*	*Ref*	*Ref*
No internet usage	0.708***	0.742***	0.754***
Year			
2010	*Ref*	*Ref*	*Ref*
2011	1.183	1.093	1.179
2012	0.962	0.821	0.994
2013	0.860	0.884	0.971
Market			
Electricity			*Ref*
Gas			0.961
Country			
Germany	*Ref*	*Ref*	*Ref*
Austria	0.679***	0.594***	0.695***
Belgium	1.684***	1.954***	2.207***
Bulgaria	0.051***	1.887***	0.876
Cyprus	-	-	-
Czech Republic	1.018	1.506***	1.400***
Ireland	1.969***	1.655***	1.944***
Denmark	1.162***	0.733***	0.993
Estonia	2.104***	0.459***	1.079
Greece	-	0.452***	0.114***
Spain	0.876	1.065	0.909
Finland	1.562***	0.434***	1.556***
France	0.609***	0.782***	0.716***
Hungary	0.170***	0.869	0.606**
Italy	1.474***	0.915	1.149
Lithuania	1.226*	-	1.142
Luxembourg	0.440***	0.571***	0.428***
Latvia	0.409***	0.635***	0.553***

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Table 5.4 – continued from previous page

VARIABLES	Electricity Consumer Switch	Natural Gas Consumer Switch	Energy Markets† Consumer Switch
Malta	-	-	-
Netherlands	1.894***	1.660***	1.618***
Poland	0.654***	0.617***	0.695***
Portugal	0.999	0.754***	0.707**
Romania	0.546***	0.624***	0.509***
Sweden	1.672***	1.079	1.864***
Slovenia	0.610***	0.794***	0.760***
Slovakia	0.863**	1.643***	1.271***
United Kingdom	1.375***	1.535***	1.510***
Comparability			
Very difficult	0.858	1.209*	1.140
Difficult	1.308***	1.517***	1.186*
Neither difficult or easy	1.097	1.274**	1.096
Easy	1.088	1.113	1.069
Very easy	*Ref*	*Ref*	*Ref*
Trust			
Strong mistrust	2.658***	2.441***	2.759***
Mistrust	2.186***	2.253***	2.382***
Neither mistrust or trust	2.071***	1.990***	2.179***
Trust	1.534***	1.532***	1.768***
Strong trust	*Ref*	*Ref*	*Ref*
Ease of switching			
Very difficult	0.218***	0.194***	0.179***
Difficult	0.219***	0.260***	0.269***
Neither difficult or easy	0.254***	0.297***	0.279***
Easy	0.490***	0.554***	0.495***
Very easy	*Ref*	*Ref*	*Ref*
Lives up to expectation			
Very poor	1.526*	1.438*	1.194
Poor	1.924***	1.471*	1.778**
Neither poor or well	1.522**	1.224	1.204
Well	1.186***	1.117*	1.136*
Very well	*Ref*	*Ref*	
Complaints			
None	*Ref*	*Ref*	*Ref*
To a retailer/provider	3.700***	4.238***	4.714***
To an official third party	6.197***	5.551***	6.361***
To friend/family	2.698***	3.876***	3.646***

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Table 5.4 – continued from previous page

VARIABLES	Electricity Consumer Switch	Natural Gas Consumer Switch	Energy Markets† Consumer Switch
Other non-energy switches			
None			*Ref*
At least one other switch			2.328***
Constant	0.119***	0.102***	0.074***
Observations	45,026	43,241	43,648
Log Likelihood	-1.7e+04	-1.5e+04	-1.5e+04

† Sub-sample of energy consumers surveyed on three or more switching markets
***p<0.01, **p<0.05, *p<0.1

In comparison to the overall model of switching in all markets, a consumer's rating of the different market components of each energy market are also found to have a highly significant role in consumer switching. As expected, the consumer ratings of 'comparability', 'trust' and 'ease of switching' for the energy markets have broadly the same effects on the likelihood of switching as the effects estimated in the broader model across all 14 switching markets. Similar to the main model, greater difficulty in comparability and stronger mistrust are associated with a higher propensity to switch, while greater difficulty in the ease of switching is associated with a lower propensity to switch. Moreover, the consumer's satisfaction with the market, measured by their rating of how the market lived up to expectation, seems to matter less for switching in the natural gas market than in the electricity market, where a poorer expectation was related to an increased inclination to switch. Complaints are also an important factor in switching for both energy markets, with the odds of switching for consumers making complaints to an official third party being over five times larger than the odds of switching for consumers with no complaints in each energy market.

It is also worth highlighting some of the differences in the estimated switching propensities for the energy markets across countries. In particular, consumers in Belgium, Ireland, the Netherlands and the UK are found to be significantly more likely to switch in both the electricity and natural gas markets compared to consumers in Germany. While alternatively, consumers in Austria, France, Luxembourg, Latvia, Poland, Romania and Slovenia are all statistically less likely to switch in both of the energy markets relative to their German counterparts. Also of relevance to the cross-country comparison of the odds of switching is the fact that some energy markets do not exist in certain countries, for example natural gas in Cyprus and Malta. Furthermore,

in other countries some markets remained monopolies across all four waves i.e. electricity in Cyprus, Greece and Malta, and gas in Lithuania. Thus, there is no variation in consumer switching to estimate these countries' relative effects.

Given that many consumers in the survey were asked about more than one switching market simultaneously, an additional model is estimated on a sub-sample of observations for energy consumers who were asked about at least three switching markets in the CMMS. This model controls for the influence that switching in other non-energy markets has on switching within the energy markets. The aim is to establish if there is an underlying propensity to switch in a consumer's preferences, where they may naturally be an active consumer and motivated to switch, or in other words, they are inherently prone to switching. The results (see Table 5.4) indicate that whether or not a consumer switches in other markets has a significant association with whether they switch in the two energy markets. If a consumer has switched in at least one other non-energy market surveyed, they are found to have a much higher odds of switching in the energy markets compared to consumers who have not switched in any other market surveyed. The odds emerge to be over twice as large in comparison. These results give greater insight into the findings of Waddams Price and Zhu (2016) that higher switching in one service is associated with switching in others and the outcome here provides some evidence that certain individuals could characteristically be 'switchers', while other consumers may be more predisposed to consumer inertia.

5.5.3 Switching heterogeneity across countries

As an important extension to this chapter, the heterogeneous effects of the socio-demographic factors and the consumer rated market components on consumer switching across countries are considered for the first time. The results from separate models estimated for each of seven different EU27 countries are shown in Table 5.5. Germany is presented because it is the baseline country in the analysis above, while Ireland, UK, Denmark, Spain, and Lithuania are presented because their consumers were found to have a much higher propensity to switch compared to German consumers. France is presented because its consumers are just as inclined to switch as German consumers. The standard errors are reported in Appendix C, Table C.3.

At an overall level, the results from the separate country models suggest that there is considerable heterogeneity in the impacts of socio-demographic factors on consumer switching across the seven countries. Ireland is the only country to show a gender differential in switching behaviour with female consumers in Ireland relatively less likely to switch than male consumers. In Ireland, Spain and France, older consumers are

significantly less likely to switch than consumers in the 35-54 year old reference category, while younger consumers are significantly more likely to switch than the 35-54 year old category in the UK, Denmark and Lithuania. For occupation, self-employed consumers in Denmark, Spain and France, together with students in Denmark, are more disposed to switching than white collar employees, whereas unemployed consumers in the UK and Lithuania are less disposed to switch alongside consumers in Germany who are house-persons or retired. Also, education plays a more important role for switching in some countries than the main model would suggest. Relative to consumers with more than 20 years in education, consumers with fewer than 15 years in education are less inclined to switch in the UK, Denmark and Lithuania. As expected, and similar to the results in the main model, consumer's accessibility to the internet is a significant factor in switching behaviour across all seven countries, where consumers with no internet usage are found to have a smaller likelihood of switching in comparison to consumers with internet usage in each country.

In considering the differences in switching across all markets in comparison to the electricity market, it is clear that there is considerable heterogeneity across countries. For example, in Germany, consumers in the mobile telephone market are more inclined to switch relative to those in the electricity market, with consumers in all other markets being significantly less likely to switch. However, in Denmark, Spain, France and Lithuania, consumers in the majority of other markets are more inclined to switch than in the electricity market with a few notable exceptions i.e. the natural gas market in Denmark and the mortgages market in Spain, France and Lithuania. For Ireland and the UK, there is even greater heterogeneity across markets, with one example being that consumers in the natural gas market in Ireland have a lower likelihood of switching than those in the electricity market, while in the UK it is found to be the opposite that holds.

In terms of consumer attitudes to the main characteristics of the market, again there is some heterogeneity across the seven countries. Consumer attitudes towards the comparability of products, services and suppliers within markets is not a significant factor in switching decisions in the UK, Spain and France, while it is more important for the other four countries examined. This could be an indicator that policies or institutions in some countries may be more effective at promoting price and quality comparisons beyond consumer perceptions. In contrast, consumer's trust in the supplier or provider is recognised to be a fundamental determinant to switching in all countries analysed and it is seen to have the largest impacts on switching in France, with consumers there having odds of switching over three times larger if they have strong mistrust in the

supplier compared to strong trust. Likewise, consumers' opinions on the difficulty in the ease of switching in markets is also a key determinant of switching across countries with consumers in the seven individual countries found to be less likely to switch, the more difficult they perceive the ease of switching. Interestingly, the results for the separate countries also suggests that consumers' beliefs on whether the market lives up to expectation is less of a significant factor for switching in Ireland and the UK, while in the other countries a 'poor' expectation belief is associated with a higher propensity to switch. Additionally, to whom a consumer complains to about a problem they encounter in a market could be considered an important determinant in switching behaviour across countries. Remarkably, the higher odds of switching attributed to complaining to friends or family is akin to, or greater than, the odds of switching when a consumer makes a complaint to the retailer or provider in all countries.

Table 5.5: Consumer switching logit results (odds ratios) by country.

VARIABLES	Ireland Consumer Switch	United Kingdom Consumer Switch	Germany Consumer Switch	Denmark Consumer Switch	Spain Consumer Switch	France Consumer Switch	Lithuania Consumer Switch
Female	0.898***	1.024	0.975	1.071	0.977	1.039	0.983
Age							
18-34 years	1.106	1.186**	0.989	1.349***	1.094	0.990	1.221**
35-54 years	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
55+ years	0.748***	0.836*	1.032	0.895	0.871***	0.825***	1.075
Occupation							
Self-employed	1.182	0.982	0.911	1.388***	1.209***	1.280**	1.120
Manager	1.148*	1.049	0.928	1.085	1.170*	1.063	1.073
White collar	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
Blue collar	0.943	0.938	0.901	1.006	1.040	0.891	0.927
Student	0.891	0.942	0.839	1.313**	0.997	1.291	0.837
House-person	0.915	0.930	0.656***	0.854	0.897	0.853	0.947
Unemployed	0.823*	0.789***	0.810*	1.139	1.130*	1.107	0.803**
Retired	0.965	1.021	0.679***	0.964	0.983	0.833	0.990
Education							
<15 years	0.949	0.906**	1.127	0.821**	0.923*	1.151	0.834***
16-19 years	0.836***	0.968	1.108	0.864**	0.939	1.027	0.925
20+ years	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
Still studying	1.047	1.094	0.980	0.872	0.889	0.646	0.958
Phone							
Fixed line only	0.839	0.803*	1.242	0.700	0.828*	0.996	0.908
Mobile only	1.054	0.819***	0.808*	1.073	1.031	1.177	1.025
Mixed	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
Internet							
Internet usage	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
No internet usage	0.702***	0.725***	0.670***	0.605***	0.682***	0.663**	0.703***
Year							
2010	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
2011	1.193	0.990	1.207*	1.305**	1.032	1.151	0.953
2012	1.131	1.136	0.504***	0.896	1.187	0.718**	1.014
2013	1.068	1.105	0.406***	1.006	1.181	0.882	1.044
Market							
Electricity	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
Bank accounts	0.439***	0.768***	0.610***	1.102***	1.504***	1.282***	1.649***

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Table 5.5 – continued from previous page

VARIABLES	Ireland Consumer Switch	United Kingdom Consumer Switch	Germany Consumer Switch	Denmark Consumer Switch	Spain Consumer Switch	France Consumer Switch	Lithuania Consumer Switch
Loans and credit	0.498***	1.117***	0.575***	1.423***	1.547***	1.415***	1.289***
Investment products	1.180***	1.756***	0.830***	1.935***	2.654***	1.377***	2.224***
Home insurance	1.076***	1.285***	0.590***	1.008	1.182***	1.084***	1.059
Vehicle insurance	1.094***	1.765***	0.994	1.167***	1.702***	1.260***	3.045***
Fixed telephone	0.734***	0.866***	0.709***	1.374***	2.504***	1.648***	3.821***
Mobile telephone	0.661***	1.010	1.078***	5.587***	3.217***	2.382***	4.599***
Internet	0.763***	0.887***	0.713***	1.504***	2.663***	1.478***	2.773***
Commercial sport	0.709***	0.921*	0.671***	1.194***	1.618***	1.340***	2.168***
Gas	0.776***	1.075***	0.839***	0.594***	1.169***	1.230***	-
Mortgages	0.237***	1.312***	0.668***	2.684***	0.442***	0.952	0.940
Private life insurance	0.624***	0.767***	0.584***	1.165***	1.313***	1.197***	1.238**
TV subscriptions	0.622***	0.764***	0.448***	2.033***	1.127***	1.194***	1.814***
Comparability							
Very difficult	1.331***	0.944	1.531***	1.456***	0.931	0.988	1.205*
Difficult	1.257*	1.235*	1.364**	1.483***	1.097	1.034	1.483***
Neither	1.063	0.923	1.395***	1.190**	1.050	1.167*	1.276***
Easy	1.097	1.036	1.080	1.295***	0.947	0.990	1.154**
Very easy	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
Trust							
Strong mistrust	2.289***	2.306***	2.107***	1.462**	2.147***	3.106***	1.491**
Mistrust	2.154***	2.071***	2.091***	1.278*	1.909***	2.563***	1.552***
Neither	1.727***	1.846***	1.940***	1.036	1.648***	2.225***	1.268***
Trust	1.269***	1.405***	1.486***	0.990	1.247**	1.428**	1.187**
Strong trust	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
Ease of switching							
Very difficult	0.209***	0.265***	0.414***	0.211***	0.339***	0.553***	0.467***
Difficult	0.299***	0.300***	0.421***	0.307***	0.379***	0.610***	0.419***
Neither	0.381***	0.311***	0.575***	0.160***	0.486***	0.567***	0.496***
Easy	0.551***	0.527***	0.636***	0.516***	0.725***	0.663***	0.695***
Very easy	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
Expectation							
Very poor	0.898	1.090	2.018***	1.847***	1.090	1.151	1.043
Poor	1.034	1.212	2.071***	1.927***	1.285**	1.810***	1.295***
Neither	0.913	0.941	1.971***	1.465***	1.002	1.621***	1.229**
Well	1.032	1.107	1.259***	1.310***	1.028	1.170*	1.219**
Very well	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*

Continued on next page

Table 5.5 – continued from previous page

VARIABLES	Ireland Consumer Switch	United Kingdom Consumer Switch	Germany Consumer Switch	Denmark Consumer Switch	Spain Consumer Switch	France Consumer Switch	Lithuania Consumer Switch
Complaints							
None	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
To a retailer/provider	2.638***	2.824***	4.661***	2.199***	3.110***	4.311***	2.171***
To an official third party	3.033***	3.467***	8.670***	1.783**	4.225***	4.623***	2.087***
To friend/family	3.427***	3.486***	3.860***	2.312***	3.327***	4.331***	2.360***
Constant	0.298***	0.213***	0.103***	0.180***	0.106***	0.043***	0.105***
Observations	27,290	27,263	27,074	27,113	26,874	27,251	23,331
Log Likelihood	-2620.59	-3.8e+04	-3.5e+04	-3224.10	-2.8e+04	-2.5e+04	-1917.36

***p<0.01, **p<0.05, *p<0.1

5.6 Conclusion

This chapter presented a micro-econometric analysis of consumer switching data from a pooled sample of the four waves from 2010 to 2013 of the European Commission's Consumer Market Monitoring Survey to examine the factors influencing consumer switching in energy markets and in the broader context of other non-energy markets and across a number of countries. It explored the role of consumers' socio-demographic characteristics together with their attitudes to the market on the propensity to switch product/service or supplier. A binary choice logit model was used to consider consumer switching across 14 switching markets for the EU 27 countries. Then, for comparison, separate logit models for consumer switching were estimated for both the electricity and natural gas markets across the EU27 countries.

Consumer attitudes, whether in the energy markets or across all markets, are found to be significant factors for consumer switching behaviour. In reflecting the costs of switching, a consumer's belief that the ease of switching is difficult is associated with a much lower propensity to switch in this study, emphasising the obstacle that switching costs pose for switching activity. This reaffirms the findings reported by the majority of the literature and provides further evidence for policymakers to intervene to help influence these beliefs by making better information on switching more widely available. Limited comparability across energy providers is also revealed to be a key determinant for switching, with consumers that find it difficult to compare electricity or natural gas products and suppliers having a larger likelihood of switching. This could indicate a greater level of uncertainty for the consumer about their current product or supplier because of the inability to make adequate comparisons and may lead to an unfavourable type of switching where consumers don't necessarily choose the best alternative, as demonstrated by Wilson and Waddams Price (2010). Accordingly, there is a role for public policy to enhance comparability amongst products and suppliers by promoting the provision of comparison literature and websites. Indeed, another important finding of this research is that accessibility to the internet for private reasons is shown to have a significantly positive impact on switching for the energy markets and for all markets in general, with consumers that have no internet access found to have a much lower odds of switching in comparison. This could highlight the internet's role as both an instrument for comparison and a mechanism for easy transition between suppliers.

In addition, a consumer's trust in, and satisfaction with, the supplier are established to be important factors for consumer switching behaviour in this study. The odds of switching for consumers with mistrust or strong mistrust in the energy supplier are

twice as large as the odds for consumers with strong trust, while dissatisfied consumers who believe that the energy service is very poor at living up to expectation are found to be considerably more likely to switch compared to consumers who are satisfied that the product/service lives up to expectation very well. Consumer complaints, which reflect the effect of severe problems with the energy markets, are found to matter most for consumer switching. This chapter shows that the odds of switching are on average over five times larger for consumers when they complain to an official third party about a problem relative to the odds of switching for consumers who never complained. It is of particular note that these consumer attitudes and complaints are also estimated to have broadly the same effects in the model across all markets. This suggests that consumer attitudes and complaints are significant determinants of switching in all markets and not just unique factors for switching in the energy sector. To retain their consumer base and attract new consumers, it is clear that suppliers must ensure they maintain a high level of trust and satisfaction and to deal with any problems effectively so as to limit consumer complaints.

A consumer's socio-demographic characteristics are revealed to have no significant association with switching in both the electricity and natural gas markets, while in contrast, the age and occupation of the consumer are found to be related to the decision to switch in markets overall. Younger consumers together with self-employed consumers are found to be more likely to switch, though older and retired consumers are found to be less likely to switch. This might support the provision of information on switching to be made more accessible to older consumers, although it is unknown how much they would actually benefit from switching in the first place. More interestingly, the results from a sub-sample analysis in the chapter indicate that for the energy markets, the odds of switching for a consumer who has switched in at least one other non-energy market are twice as large relative to the odds of switching for a consumer who hasn't switched in any other market surveyed. There could be two possible explanations for this; firstly, certain consumers are inherently more prone to being active consumers and are naturally motivated to switch or secondly, other experience in switching counts toward making further switching in other markets a more convenient and manageable exercise. From a policy perspective in the first instance, there is not much policymakers can do other than encourage consumers to be more active in the market, while in the second instance there is a great deal that can be done by public policy. One example is to give greater responsibility to competition authorities to help demonstrate the process of switching.

A further contribution of this chapter is that it explored the factors influencing

switching across seven EU countries independently. Across these countries, some heterogeneity is found in the role of consumers' attitudes to the market on switching decisions. Attitudes towards the comparability of products is not a significant factor for the switching decision in the UK, Spain and France, whereas it is important for the other countries examined. Also, consumers' beliefs on the degree to which the market lives up to expectation matters less for switching in Ireland and the UK. Further heterogeneity is established in terms of the impacts of consumers' socio-demographic characteristics over countries. For example, older consumers are less inclined to switch in Ireland, Spain and France, while younger consumers are more likely to switch in the UK, Denmark and Lithuania. EU policymakers could learn much from the institutions and social norms in place in the individual Member States where some countries may have a distinct advantage over others in facilitating switching.

To conclude, this chapter has shown that consumers' attitudes to the main characteristics of the market are highly significant factors in explaining consumer switching behaviour in both energy markets and in switching markets more generally in Europe. In contrast, consumers' socio-demographic characteristics are not significant factors for the switching choice in the individual energy markets, though they do contribute to the switching decision in markets generally, with age and occupation both found to play a role. Moreover, consumer complaints were found to have the largest effect on consumer switching among the factors examined, while switching in energy markets is also revealed to be significantly associated with switching in non-energy markets. Finally, there is strong evidence of heterogeneity across EU Member States in the effects of consumers' socio-demographic characteristics and attitudes on consumer switching.

Chapter 6

Conclusion

6.1 Main Findings and Policy Implications

The European Commission recently introduced its strategy for a resilient 'Energy Union', including a forward looking climate change policy, where the primary objective is to provide EU consumers with secure, sustainable, competitive and affordable energy. The EU plans to move away from an economy dependent on fossil fuels and the Energy Union would place EU citizens at the heart of this energy transition to a low carbon and climate friendly economy. More specifically, the Energy Union is concerned with engaging consumers to help support the energy transformation through their active role and participation in energy markets, especially within the residential sector, which constitutes a significant share of total EU energy consumption.

Within this broad context, this thesis examined issues relating to consumer engagement and heterogeneity in residential energy demand. It had four specific goals, which were addressed in four separate empirical essays. The first essay (Chapter 2) analysed and explained the determinants of residential gas demand and identified the average effect of a demand side management (DSM) programme on household gas consumption. The second essay (Chapter 3) systematically explored the heterogeneity and habit formation in the effect of the DSM programme identified in Chapter 2. Both Chapter 2 and 3 highlighted the effectiveness of smart metering enabled DSM for the residential consumer's engagement in the control and management of their natural gas consumption. Following this, and moving the focus to total household energy consumption, the third essay (Chapter 4) looked at the relationship between energy expenditure and income. This chapter explored the variation in the income elasticity of household energy demand across the energy expenditure distribution and considered the context dependent implications for social policies such as income supports for protecting and

engaging vulnerable consumers. Finally, the fourth essay (Chapter 5) examined the factors influencing consumer switching in European energy markets, where switching is understood to play a key role in creating competitive markets.

Focusing on Chapter 2, this research presented a micro-econometric panel analysis of the household daily gas consumption data from Ireland's Smart Metering Consumer Behavioural Trial to examine the determinants of residential gas demand in Ireland. In contrast to the previous literature, Chapter 2 explicitly examined residential gas demand, utilised high frequency micro-data, controlled for a wide range of weather-related variables and thus makes a substantial contribution to the literature. The results from the analysis in Chapter 2 provide important evidence that the energy efficiency measures, together with the dwelling and the socio-economic characteristics of the households, are highly significant determinants of residential gas demand in Ireland. While not surprising, the weather-related variables are found to be the most influential factors on the household's daily gas consumption and for that reason should be included in any natural gas demand analysis.

In addition, Chapter 2 employed a quasi-experimental methodology using difference-in-differences estimation to identify, for the first time, the effectiveness of a DSM programme in reducing household gas use. Indeed, the chapter found that the DSM stimuli tested as part of the trial are overall quite effective at engaging households to reduce their daily gas consumption. The results showed that the average treatment effect (ATE) is a reduction in household natural gas consumption of 1.54 kilowatt-hours (kWh) per day, and with a consumer base of over half a million gas using households in Ireland, these energy savings are economically significant. This finding also helps strengthen the argument for such DSM programmes to be implemented more widely across the residential sector to assist consumer engagement, increase energy efficiency and contribute to carbon abatement targets and climate change mitigation in general.

While Chapter 2 identified the average effect of participation in the DSM programme on household gas demand, Chapter 3 built on this analysis and explored the heterogeneity and habit formation in this average effect using the same micro-data. It is the first study to consider heterogeneity in the effect of DSM stimuli across such a broad range of household characteristics and the only analysis internationally to reflect such heterogeneity in the case of residential gas demand. To examine the heterogeneous treatment effects, the ATEs were allowed to vary systematically across different groups of households categorised by their socio-economic, household level and dwelling characteristics in a random effects model.

Chapter 3 found that the demand side stimuli have very different effects depending

upon household characteristics, with older and larger households in older and larger dwellings found to be significantly more responsive to the information stimuli. Moreover, the average effects of the stimuli are discovered to be more homogeneous across dwellings' energy characteristics, with the notable exception of households in dwellings with no external wall insulation. These households are significantly more receptive to the stimuli compared to households in dwellings with external wall insulation. Similarly, the chapter showed that households with the largest potential savings and greatest capacity to reduce their gas use were similar to households that were most responsive to the information stimuli. This suggests that there are more energy savings and carbon emissions reductions to be gained by targeting the feedback stimuli on households with the most amenable characteristics.

In terms of habit formation, Chapter 3 studied the effect of the overall demand side stimulus across time, with the ATE allowed to vary over the bimonthly billing cycles in the trial period in a fixed effects model. The results indicated that there is an initial learning or adjustment period to the stimuli of two bimonthly billing cycles and thereafter, the effects were found to be more pronounced and persistent, though diminishing, across the rest of the treatment period. This is an encouraging finding with respect to the persistence of benefits from DSM programmes. However, policymakers should expect to observe a modest time lag before programme effects become apparent. Given that the household characteristics associated with a high baseline gas use were the same characteristics for which the DSM was most effective, Chapter 3 also estimated the quantile treatment effects across the distribution of daily residential gas consumption, using a difference-in-differences quantile regression approach. The stimuli were found to have no statistically significant effect on a household's gas use in the lower quantiles or the very top quantile (ninth decile) examined, while there was some small variation found in the effect for the other quantiles.

Following on from this, Chapter 4 looked at the relationship between energy expenditure and income, and in particular explored heterogeneity in this relationship across the distribution of energy expenditure. While it is generally assumed in the literature that the income elasticity of household energy demand at mean income is of most interest, it is clear that not all policy is concerned with the average household and is more likely to target low or high energy consumption households. Thus, it is important to account for the context dependent variation in the elasticity and to make use of the most applicable elasticity in estimating the impact of any related policy measure. In this regard, this chapter aimed to fill this gap in the literature by using Irish household budget survey data to examine the variation in the income elasticity of household

energy demand across the entire energy expenditure distribution using a two stage quantile regression analysis. It compared these elasticities across high and low energy consumption profiles, as well as to the benchmark constant mean elasticity.

The main finding of Chapter 4 was that there is a large variation in the income elasticity of household energy demand across low and high energy consumption contexts and the results suggest that households with a low energy expenditure could be up to 3.6 times more responsive to a one percent increase in their incomes than households with a high energy expenditure. This chapter also found that there is a distinct difference between the benchmark constant elasticity estimate and the quantile elasticities, with the bottom 10% shown to be almost 2.5 times more sensitive to a one percent increase in their incomes than the constant mean elasticity would imply. These results have some important policy implications. For example, the provision of income supports is a widely used policy mechanism to alleviate the symptoms of fuel poverty and the evidence from this chapter suggests that such supports could have a much greater importance for reducing the level of fuel poverty, whilst protecting and engaging vulnerable consumers, than previous research has revealed. Moreover, given the estimated difference in the elasticity between the bottom 10% and top 10% in the energy expenditure distribution, it could be argued that such transfer payments could be more strongly advocated for.

Recognising the importance of consumer engagement in energy markets through switching, the fourth essay (Chapter 5) examined the factors influencing switching in European energy markets. It used data from a pooled sample of four independent cross-sections of a large scale EU market monitoring survey, which monitored 14 switching markets in total including the electricity and natural gas markets. The resulting sample for the purpose of the analysis is the largest by far of any sample used in empirical studies of consumer switching. A binary logit model was estimated for overall switching across the 14 European markets, together with separate models for switching in both the electricity and natural gas markets for comparison.

Consumer attitudes were found to be very significant factors for consumer switching behaviour whether in the energy markets or across all switching markets. For example, the results suggested that when consumers perceive the ease of switching to be difficult, they are estimated to have a much lower propensity to switch. This demonstrates the barrier that perceived switching costs create for switching and presents an argument for the provision of better information on switching to assist in countering such beliefs. In another example, limited comparability across energy service suppliers was shown to be a significant factor for switching. Remarkably, this finding indicated that consumers who find it difficult to compare services/products or suppliers were much more

inclined to switch. One reason for this could be that limited comparability may lead to uncertainty for the consumer around their current choice of service, which in turn could influence them to switch. As a result, public policy should endeavour to improve service comparability through the promotion of comparison literature and websites, especially since the analysis in Chapter 5 also revealed that private access to the internet is positively associated with consumer switching in general.

Moreover, a consumer's trust in, and satisfaction with, the supplier were also found to be related to consumer switching, where greater trust in the provider and greater satisfaction, where the service lived very well up to expectation, were shown to be associated with a lower likelihood of switching. Interestingly, consumer complaints was found to matter most for consumer switching among the factors considered, with complaints to an official third party linked to very large odds of switching. In terms of socio-demographic characteristics, age and occupation were revealed to be significant factors associated with the decision to switch in markets overall, though they were shown to have no significant influence on switching in the individual energy markets.

In an extension to the main model in Chapter 5, a sub-sample analysis was employed to provide evidence on whether switching in other non-energy markets influences switching in energy markets. The results from this sub-sample analysis suggested that the odds of switching in energy markets increased for consumers who had switched in at least one other non-energy market. Indeed, this could indicate that either these consumers are inherently more prone to being active and are naturally motivated to switch, or that some switching experience makes further switching less burdensome. Finally in Chapter 5, separate country models were estimated to compare the heterogeneous effects of the different influential factors on switching across countries. The results showed that across countries there was some heterogeneity with respect to the influence of consumer attitudes on switching, while the estimated effects of consumers' socio-demographic characteristics on the propensity to switch were found to be much more heterogeneous over the countries examined.

6.2 Limitations and Future Research

Given that income could not be controlled for in the analysis in Chapters 2 and 3 because of the high rate of non-response to the income question in the smart metering trial, it is important for future research to include appropriate measures of household income to separate out the income effect and remove any potential bias to other coefficients arising from its omission. Furthermore, with weather-related variables found to be the most

influential factors in gas demand in this research, it might also be worthwhile for future research to allow for non-linear weather effects in such models by following an approach like the one utilised in Conniffe (1996), together with establishing the impact of the long run weather on residential gas demand. Moreover, much research also remains to be done on other household factors that may determine residential gas demand, for which there was incomplete data in the smart metering trial. These factors include the energy efficiency characteristics of dwellings, the heating controls employed in each household, as well as the efficiency of the appliances used. Finally for Chapters 2 and 3, while the overall DSM programme was shown to be quite effective in reducing household gas use, the effects of the individual stimuli employed in the trial could not be estimated with much confidence due to a comparatively smaller sample size for each separate stimulus. There is a need for research to methodically verify, with increased power, the effectiveness of the different individual stimuli employed in the DSM programme so that any future implemented programmes can be made more efficient.

In Chapter 4 the quantile regression approach employed was based on the 'conditional method', whereby the effect of an independent variable on a quantile of the outcome distribution is conditional on specific values of the other covariates. For future research it would be interesting to examine if there is any difference in results from the application of the 'unconditional method', which marginalises the effect of an independent variable over the distributions of the other covariates. Given that there are few covariates in Chapter 4, the conditional method is likely to be appropriate here. Additionally for Chapter 4, publication bias could be highlighted as a concern in the estimation of the income elasticity of energy demand. Conventional wisdom implies that the income elasticity of household energy demand should be positive and, therefore, insignificant or negative estimates could be discarded, resulting in an upward bias in the overall literature. Funnel plots are a method of graphically testing for publication bias - see, for example, Havranek and Kokes (2015). The graph plots individual estimates of the income elasticity on the x-axis and the inverse of the standard error of the estimate on the y-axis, and so, the most precise estimates in the literature will be presented at the top of the funnel, while the less precise estimates will be more dispersed. A symmetric funnel is an indication that there is no publication bias in the literature. The research in Chapter 4 endeavoured to produce such a funnel plot including the benchmark elasticities estimated in its analysis. However, since the vast majority of the literature estimating income elasticities of total household energy demand does not report the standard errors of the elasticities, a reasonable funnel plot could not be produced. This could be seen as a limitation of the literature.

From an empirical perspective, omitted variable bias driven by unobserved heterogeneity may be an issue for drawing causal inferences from the analysis in Chapter 5. While the empirical work endeavoured to control for all likely determinants, the dataset was constrained by the availability of certain variables. For future research it would be useful to have a longitudinal dimension to the analysis, in order to control for consumers' unobserved individual-specific heterogeneity and previous switching history. The analysis in Chapter 5 was unable to examine the effect that past switching has on the propensity to switch now, and there was evidence to suggest that some of the variables examined could be confounded by past switching i.e. consumer comparability across products and suppliers. Given that the market monitoring dataset did include many consumers that were asked about more than one switching market, there is a future opportunity to consider a fixed effects estimator, where unobserved individual-level heterogeneity that is constant across markets could be taken into account. It would also be useful for any further study to include consumers' incomes, together with their levels of consumption of the various goods and services, to remove any potential bias in the results caused by their omission.

Another caveat to the analysis from Chapter 5 is that the data used did not contain any information on the bundling of services. Telecommunication and energy services are becoming increasingly available as bundled services, e.g. a combined electricity and gas contract, and so it is necessary to control for any effect that bundling may have on the propensity to switch. Finally, much research also remains to be done on other factors that may influence consumer switching, such as the different information and purchasing channels used to switch. For example, it might make a large difference to switching propensities and the optimality of choices made if consumers used impartial price comparison websites versus buying from door-to door salespeople, and future research could address this issue.

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Appendix A

Supplementary Material for Chapter 2

Table A.1: Regression results from the random effects model (2.1) of daily gas usage with and without outliers

VARIABLES	All observations Daily Gas Usage	Without outliers Daily Gas Usage
Female	0.021	0.029
	(1.009)	(1.008)
Age		
18-25 years	-5.482	-5.479
	(6.804)	(6.797)
26-35 years	-4.945***	-4.932***
	(1.364)	(1.363)
36-45 years	*Ref*	*Ref*
46-55 years	2.2	2.213
	(1.449)	(1.448)
56-65 years	1.9	1.907
	(1.831)	(1.83)
65+ years	5.197*	5.225*
	(2.883)	(2.88)
Refused	7.608	7.519
	(4.827)	(4.75)
Education		
None	-5.015	-5.01
	(4.269)	(4.268)
Primary	-4.947**	-4.945**
	(2.181)	(2.18)
Junior Cert	-0.608	-0.598
	(1.583)	(1.583)
Leaving Cert	-1.351	-1.345
	(1.266)	(1.265)
Third Level	*Ref*	*Ref*
Refused	0.766	0.72
	(2.737)	(2.723)
Employment Status		
Employee	*Ref*	*Ref*
Self-employed (employees)	8.731***	8.706***
	(2.742)	(2.738)
Self-employed (no employees)	4.357*	4.351*
	(2.489)	(2.486)
Unemployed	-0.3	-0.3
	(1.638)	(1.638)

Continued on next page

Table A.1 – continued from previous page

VARIABLES	All observations Daily Gas Usage	Without outliers Daily Gas Usage
Retired	2.096	2.082
	(2.308)	(2.304
Care Giver	6.92	6.927
	(6.948)	(6.95)
No. of Household Members		
1 Person	-7.608***	-7.606***
	(1.489)	(1.488)
2-3 People	*Ref*	*Ref*
4-5 People	2.690**	2.68**
	(1.171)	(1.17)
6+ People	3.829	3.849
	(3.328)	(3.329)
Tenure (Rented)	-7.013***	-7.011***
	(1.944)	(1.945)
House Type		
Apartment	-5.762	-5.765
	(3.551)	(3.552)
Semi-Detached	*Ref*	*Ref*
Detached	4.230***	4.238***
	(1.626)	(1.625)
Terraced	-1.89	-1.887
	(1.289)	(1.289)
Bungalow	6.573***	6.584***
	(2.475)	(2.475)
Number of Bedrooms		
1-2 Bedrooms	-3.173*	-3.177*
	(1.897)	(1.897)
3 Bedrooms	*Ref*	*Ref*
4 Bedrooms	10.27***	10.254***
	(1.212)	(1.211)
5+ Bedrooms	20.98***	20.922***
	(3.041)	(3.041)
Period House Built		
Pre 1900	12.62***	12.59***
	(4.069)	(4.069)
1901-1940	8.353***	8.34***
	(2.109)	(2.104)

Continued on next page

Table A.1 – continued from previous page

VARIABLES	All observations Daily Gas Usage	Without outliers Daily Gas Usage
1941-1960	4.308**	4.319**
	(2.146)	(2.145)
1961-1980	6.336***	6.347***
	(1.498)	(1.497)
1980-2000	*Ref*	*Ref*
2001-2008	0.26	0.267
	(1.325)	(1.325)
Weather		
Heating Degree Days	4.699***	4.696***
	(0.0596)	(0.059)
Sunshine Hours	-1.039***	-1.037***
	(0.0183)	(0.0183)
Cloud Cover	0.817***	0.824***
	(0.0319)	(0.032)
Rainfall	0.138***	0.137***
	(0.00962)	(0.01)
Wind Speed	0.947***	0.947***
	(0.0141)	(0.014)
Time		
Weekend Day	0.661***	0.659***
	(0.124)	(0.124)
Public Holiday	3.041***	2.954***
	(0.272)	(0.268)
Treatment Period	-1.344**	-1.37**
	(0.543)	(0.542)
Treatment Group	-0.117	-0.111
	(1.373)	(1.373)
TreatmentGroup*TreatmentPeriod	-1.537**	-1.528**
	(0.758)	(0.757)
Winter	22.06***	22.056***
	(0.341)	(0.341)
Spring	10.69***	10.7***
	(0.239)	(0.238)
Autumn	3.394***	3.405***
	(0.142)	(0.412)
Dwelling Characteristics		
Double Glazing	-0.104	-0.091
	(2.263)	(2.262)

Continued on next page

Table A.1 – continued from previous page

VARIABLES	All observations Daily Gas Usage	Without outliers Daily Gas Usage
Attic Insulation		
<5 years	-2.196*	-2.209*
	(1.137)	(1.136)
>5 years	*Ref*	*Ref*
None	-4.319**	-4.31**
	(2.141)	(2.14)
Dont Know	-1.129	-1.13
	(2.766)	(2.766)
External Wall Insulation		
Yes	*Ref*	*Ref*
No	4.537***	4.538***
	(1.291)	(1.29)
Dont Know	1.17	1.174
	(1.369)	(1.369)
Boiler Service		
Never	-4.218**	-4.204**
	(1.834)	(1.833)
Every 2-3 years	-2.266**	-2.253**
	(1.037)	(1.036)
Every year	*Ref*	*Ref*
Lagging Jacket	-1.051	-1.035
	(1.629)	(1.626)
Booster Button	1.903*	1.895*
	(1.071)	(1.07)
Fire Effects Gas Fire	2.555**	2.545**
	(1.01)	(1.009)
Constant	-18.09***	-18.151***
	(3.385)	(3.384)
Observations	636,559	636,539
Number of ID	1,181	
R^2	0.585	0.586

Cluster robust standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

Table A.2: Regression results from the random effects models of daily gas usage with standard errors reported.

VARIABLES	(1) Daily Gas Usage	(2) Daily Gas Usage	(3) Daily Gas Usage
Female	-0.0788	-0.0506	0.0215
	(0.997)	(0.997)	(1.009)
Age			
18-25 years	-6.846	-7.146	-5.482
	(5.258)	(5.305)	(6.804)
26-35 years	-5.075***	-5.081***	-4.945***
	(1.389)	(1.382)	(1.364)
36-45 years	*Ref*	*Ref*	*Ref*
46-55 years	2.502*	2.531*	2.2
	(1.451)	(1.45)	(1.449)
56-65 years	2.412	2.469	1.9
	(1.848)	(1.847)	(1.831)
65+ years	5.833**	5.841**	5.197*
	(2.935)	(2.935)	(2.883)
Refused	9.377**	9.588**	7.608
	(4.781)	(4.772)	(4.827)
Education			
None	-5.773	-5.744	-5.015
	(4.361)	(4.385)	(4.269)
Primary	-4.347**	-4.354**	-4.947**
	(2.188)	(2.197)	(2.181)
Junior Cert	-0.365	-0.384	-0.608
	(1.611)	(1.607)	(1.583)
Leaving Cert	-1.069	-1.089	-1.351
	(1.29)	(1.285)	(1.266)
Third Level	*Ref*	*Ref*	*Ref*
Refused	0.579	0.459	0.766
	(2.784)	(2.784)	(2.737)
Employment Status			
Employee	*Ref*	*Ref*	*Ref*
Self-employed (employees)	8.108***	8.217***	8.731***
	(2.824)	(2.837)	(2.742)
Self-employed (no employees)	3.824	3.912	4.357*
	(2.56)	(2.558)	(2.489)
Unemployed	-0.186	-0.0932	-0.3
	(1.632)	(1.634)	(1.638)

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Table A.2 – continued from previous page

VARIABLES	(1) Daily Gas Usage	(2) Daily Gas Usage	(3) Daily Gas Usage
Retired	2.322	2.309	2.096
	(2.337)	(2.338)	(2.308)
Care Giver	6.346	6.257	6.92
	(6.914)	(6.943)	(6.948)
No. of Household Members			
1 Person	-7.465***	-7.528***	-7.608***
	(1.546)	(1.548)	(1.489)
2-3 People	*Ref*	*Ref*	*Ref*
4-5 People	2.510**	2.516**	2.690**
	(1.183)	(1.182)	(1.171)
6+ People	3.565	3.439	3.829
	(3.302)	(3.302)	(3.328)
Tenure (Rented)	-7.585***	-7.678***	-7.013***
	(1.87)	(1.871)	(1.944)
House Type			
Apartment	-6.910*	-6.975*	-5.762
	(3.705)	(3.718)	(3.551)
Semi-Detached	*Ref*	*Ref*	*Ref*
Detached	4.001**	3.983**	4.230***
	(1.652)	(1.65)	(1.626)
Terraced	-1.892	-1.865	-1.89
	(1.309)	(1.309)	(1.289)
Bungalow	5.590**	5.553**	6.573***
	(2.566)	(2.571)	(2.475)
Number of Bedrooms			
1-2 Bedrooms	-3.611*	-3.512*	-3.173*
	(1.912)	(1.926)	(1.897)
3 Bedrooms	*Ref*	*Ref*	*Ref*
4 Bedrooms	10.55***	10.60***	10.27***
	(1.23)	(1.227)	(1.212)
5+ Bedrooms	20.30***	20.37***	20.98***
	(3.087)	(3.092)	(3.041)
Period House Built			
Pre 1900	13.52***	13.42***	12.62***
	(4.061)	(4.093)	(4.069)
1901-1940	9.606***	9.532***	8.353***
	(1.986)	(1.995)	(2.109)
1941-1960	5.856***	5.823***	4.308**
	(1.999)	(2.005)	(2.146)
1961-1980	7.468***	7.424***	6.336***

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Table A.2 – continued from previous page

VARIABLES	(1) Daily Gas Usage	(2) Daily Gas Usage	(3) Daily Gas Usage
	(1.423)	(1.421)	(1.498)
1980-2000	*Ref*	*Ref*	*Ref*
2001-2008	-0.818	-0.779	0.26
	(1.33)	(1.324)	(1.325)
Weather			
Heating Degree Days		4.699***	4.699***
		(0.0596)	(0.0596)
Sunshine Hours		-1.039***	-1.039***
		(0.0183)	(0.0183)
Cloud Cover		0.817***	0.817***
		(0.0319)	(0.0319)
Rainfall		0.138***	0.138***
		(0.00962)	(0.00962)
Wind Speed		0.947***	0.947***
		(0.0141)	(0.0141)
Time			
Weekend Day		0.661***	0.661***
		(0.124)	(0.124)
Public Holiday		3.041***	3.041***
		(0.272)	(0.272)
Treatment Period		-1.344**	-1.344**
		(0.543)	(0.543)
Treatment Group		-0.0798	-0.117
		(1.383)	(1.373)
TreatmentGroup*TreatmentPeriod		-1.537**	-1.537**
		(0.758)	(0.758)
Winter		22.06***	22.06***
		(0.341)	(0.341)
Spring		10.69***	10.69***
		(0.239)	(0.239)
Autumn		3.394***	3.394***
		(0.142)	(0.142)
Dwelling Characteristics			
Double Glazing			-0.104
			(2.263)
Attic Insulation			
<5 years			-2.196*
			(1.137)
>5 years			*Ref*
None			-4.319**
			(2.141)

Continued on next page

Table A.2 – continued from previous page

VARIABLES	(1) Daily Gas Usage	(2) Daily Gas Usage	(3) Daily Gas Usage
Dont Know			-1.129
			(2.766)
External Wall Insulation			
Yes			*Ref*
No			4.537***
			(1.291)
Dont Know			1.17
			(1.369)
Boiler Service			
Never			-4.218**
			(1.834)
Every 2-3 years			-2.266**
			(1.037)
Every year			*Ref*
Lagging Jacket			-1.051
			(1.629)
Booster Button			1.903*
			(1.071)
Fire Effects Gas Fire			2.555**
			(1.01)
Constant	38.19***	-18.11***	-18.09***
	(1.439)	(1.775)	(3.385)
Observations	636,559	636,559	636,559
Number of ID	1,181	1,181	1,181
R^2	0.069	0.58	0.585

Cluster robust standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

Appendix B

Supplementary Material for Chapter 3

Table B.1: Proportion of households in the different variable categories for control and overall treatment groups including χ^2 test statistics for the equality of proportions.

		Control %	Treatment %	χ^2 Statistic (p-value)
Female		47.0	48.2	0.194
				(0.660)
Age				3.469
<36 years		14.7	14.7	(0.483)
36-45 years	*Ref*	27.2	27.9	
46-55 years		23.2	23.9	
56-65 years		14.9	17.3	
65+ years or Refused		20.0	16.2	
Education				3.269
None or Primary		8.5	8.6	(0.514)
Junior Cert		13.2	12.3	
Leaving Cert		23.5	22.8	
Third Level	*Ref*	48.7	52.1	
Refused		6.1	4.2	
Employment Status				8.387
Employee	*Ref*	59.4	57.8	(0.039)
Self-employed		9.0	13.4	
Unemployed		5.9	7.5	
Retired or Care Giver		25.7	21.3	
Number of Household Members				2.379
1 Person		18.4	15.2	(0.304)
2-3 People	*Ref*	49.6	50.8	
4+ People		32.0	34.0	
Tenure (Rented)		8.3	6.1	2.329
				(0.127)
House Type				0.294
Apartment or Terraced		23.9	22.9	(0.863)
Semi-Detached	*Ref*	55.5	55.4	
Detached or Bungalow		20.6	21.7	

		Control %	Treament %	χ^2 Statistic (p-value)
Number of Bedrooms				4.527
1-2 Bedrooms		9.0	9.9	(0.210)
3 Bedroom	*Ref*	55.0	49.3	
4 Bedrooms		31.2	34.2	
5+ Bedrooms		4.8	6.6	
Period House Built				5.175
Pre 1940		13.6	11.5	(0.270)
1941-1960		11.0	10.2	
1961-1980		23.7	20.9	
1981-2000	*Ref*	28.7	29.4	
2001-2008		23.0	28.0	
Dwelling Characteristics:				
Attic Insulation				8.051
<5 years		25.0	27.6	(0.045)
>5 years	*Ref*	62.5	63.8	
None		8.5	6.9	
Don't Know		4.0	1.7	
External Wall Insulation				0.424
Yes	*Ref*	46.9	48.3	(0.809)
No		36.4	36.3	
Don't Know		16.7	15.4	
Boiler Service				0.770
Never		8.1	9.5	(0.680)
Every 2-3 years		36.6	35.6	
Every year	*Ref*	55.3	54.9	
Double Glazing		93.2	94.5	0.904
Lagging Jacket		89.7	88.5	0.397
Booster Button		40.4	41.1	0.060
Fire Effects Gas Fire		48.0	44.9	1.185

Ref is the omitted reference category.

Table B.2: Estimated HTEs for each variable category from individual random effects models, unconditional on other characteristics.

VARIABLES	Daily Gas Usage	Std. Errors†	VARIABLES	Daily Gas Usage	Std. Errors†
Treatment			**Period House Built*D$_{it}$**		
λ_t	-	-	Pre 1940	-4.942***	1.895
α_i	-	-	1941-1960	-2.553*	1.633
D$_{it}$	-	-	1961-1980	-5.152***	1.144
			1981-2000	*Ref*	
Female*D$_{it}$	1.221	0.882	2001-2008	1.250*	1.024
Age*D$_{it}$			**Weather**		
<36 years	5.101***	1.053	Heating Degree Days	-	-
36-45 years	*Ref*		Sunshine Hours	-	-
46-55 years	-3.405***	1.215	Cloud Cover	-	-
56-65 years	-4.927***	1.223	Rainfall	-	-
65+ years or Refused	-4.424***	1.48	Wind Speed	-	-
Education*D$_{it}$			**Time*D$_{it}$**		
None or Primary	1.547	1.323	Weekend Day	-	-
Junior Cert	-1.468	1.376	Public Holiday	-	-
Leaving Cert	0.585	1.057	Winter	-	-
Third Level	*Ref*		Spring	-	-
Refused	-2.225	2.481	Autumn	-	-
Employment Status*D$_{it}$			**Dwelling Characteristics*D$_{it}$**		
Employee	*Ref*		Double Glazing	-1.468	2.125
Self-employed	-3.714***	1.277	Lagging Jacket	-2.587**	1.157
Unemployed	2.014	1.425	Booster Button	-1.1	0.897
Retired or Care Giver	-3.917***	1.275	Fire Effects Gas Fire	-2.545***	0.896

Continued on next page

Table B.2 – continued from previous page

VARIABLES	Daily Gas Usage	Std. Errors†	VARIABLES	Daily Gas Usage	Std. Errors†
No. of Household Members*D$_{it}$			**Attic Insulation*D$_{it}$**		
1 Person	5.603***	1.337	<5 years	1.501	1.038
2-3 People	*Ref*		>5 years	*Ref*	
4+ People	-2.81***	0.942	None	3.885***	1.487
			Don't Know	7.622***	2.891
Tenure*D$_{it}$ (Rented)	7.444***	1.307			
			External Wall Insulation*D$_{it}$		
House Type*D$_{it}$			Yes	*Ref*	
Apartment or Terraced	4.1***	1.093	No	-3.676***	0.987
Semi-Detached	*Ref*		Don't Know	2.005*	1.143
Detached or Bungalow	-4.304***	1.165			
			Boiler Service*D$_{it}$		
Number of Bedrooms*D$_{it}$			Never	4.734***	1.468
1-2 Bedrooms	5.64***	1.100	Every 2-3 years	0.953	0.944
3 Bedrooms	*Ref*		Every year	*Ref*	
4 Bedrooms	-7.37***	0.936			
5+ Bedrooms	-14.664***	2.049	**Constant**	-	-
			Observations		697,466
			Number of ID		1,294

†Cluster robust std. errors at the household level
***p<0.01, **p<0.05, *p<0.1

Appendix C

Supplementary Material for Chapter 5

Table C.1: Consumer switching logit results (odds ratios) weighted by EU27 population with standard errors reported.

VARIABLES	(1) Consumer Switch	(2) Consumer Switch	(3) Consumer Switch
Female	0.953**	0.945***	0.986
	(0.015)	(0.014)	(0.015)
Age			
18-34 years	1.120***	1.110***	1.122***
	(0.029)	(0.025)	(0.026)
35-54 years	*Ref*	*Ref*	*Ref*
55+ years	0.923***	0.909***	0.916***
	(0.020)	(0.019)	(0.019)
Occupation			
Self-employed	1.269***	1.151***	1.080***
	(0.032)	(0.022)	(0.023)
Manager	1.143***	1.119***	1.105***
	(0.038)	(0.027)	(0.028)
White collar	*Ref*	*Ref*	*Ref*
Blue collar	1.056	0.931***	0.932***
	(0.031)	(0.018)	(0.019)
Student	0.981	0.935	0.959
	(0.063)	(0.048)	(0.047)
House-person	0.958	0.856***	0.864***
	(0.028)	(0.021)	(0.021)
Unemployed	1.242***	1.008	0.952
	(0.057)	(0.028)	(0.026)
Retired	0.989	0.886***	0.912***
	(0.032)	(0.025)	(0.026)
Education			
<15 years	1.127**	0.999	0.978
	(0.049)	(0.024)	(0.022)
16-19 years	1.008	0.993	0.981
	(0.027)	(0.019)	(0.017)
20+ years	*Ref*	*Ref*	*Ref*
Still studying	1.078	1.007	1.005
	(0.060)	(0.045)	(0.044)
Phone			
Fixed line only	0.812***	0.904*	0.928
	(0.039)	(0.042)	(0.042)

Continued on next page

Table C.1 – continued from previous page

VARIABLES	(1) Consumer Switch	(2) Consumer Switch	(3) Consumer Switch
Mobile only	1.124**	0.989	0.987
	(0.042)	(0.024)	(0.022)
Mixed	*Ref*	*Ref*	*Ref*
Internet			
Internet usage	*Ref*	*Ref*	*Ref*
No internet usage	0.695***	0.669***	0.707***
	(0.023)	(0.017)	(0.016)
Year			
2010	*Ref*	*Ref*	*Ref*
2011	0.951	1.005	0.997
	(0.031)	(0.035)	(0.029)
2012	0.794***	0.856**	0.886***
	(0.038)	(0.046)	(0.037)
2013	0.792***	0.856**	0.891**
	(0.044)	(0.051)	(0.043)
Market			
Electricity		*Ref*	*Ref*
Bank accounts		1.121	0.967
		(0.159)	(0.126)
Loans and credit		0.975	0.961
		(0.141)	(0.123)
Investment products		1.724***	1.650***
		(0.225)	(0.202)
Home insurance		0.817	0.825
		(0.155)	(0.147)
Vehicle insurance		1.420*	1.408*
		(0.220)	(0.198)
Fixed telephone		1.487**	1.393*
		(0.223)	(0.191)
Mobile telephone		2.175***	1.825***
		(0.336)	(0.254)
Internet		1.596**	1.339*
		(0.228)	(0.180)
Commercial sport		1.095	1.147
		(0.148)	(0.140)
Gas		0.903	0.962
		(0.158)	(0.141)

Continued on next page

Table C.1 – continued from previous page

VARIABLES	(1) Consumer Switch	(2) Consumer Switch	(3) Consumer Switch
Mortgages		0.815	0.881
		(0.140)	(0.150)
Private life insurance		0.865	0.915
		(0.116)	(0.108)
TV subscriptions		1.335	1.151
		(0.232)	(0.185)
Country			
Germany		*Ref*	*Ref*
Austria		1.288*	1.135
		(0.126)	(0.104)
Belgium		1.859***	1.786***
		(0.188)	(0.153)
Bulgaria		2.199***	1.803***
		(0.270)	(0.223)
Cyprus		1.066	1.009
		(0.167)	(0.142)
Czech Republic		1.640***	1.479***
		(0.156)	(0.136)
Ireland		2.099***	1.812***
		(0.231)	(0.206)
Denmark		2.299***	2.222***
		(0.351)	(0.303)
Estonia		1.317*	1.324*
		(0.174)	(0.147)
Greece		1.452***	1.370**
		(0.157)	(0.142)
Spain		2.516***	1.872***
		(0.227)	(0.155)
Finland		1.992***	1.868***
		(0.241)	(0.191)
France		0.929	0.983
		(0.073)	(0.071)
Hungary		2.073***	1.778***
		(0.308)	(0.252)
Italy		1.843***	1.633***
		(0.164)	(0.134)
Lithuania		2.651***	2.286***
		(0.249)	(0.214)
Luxembourg		0.674***	0.718***
		(0.065)	(0.061)
Latvia		2.089***	2.070***
		(0.234)	(0.196)

Continued on next page

Table C.1 – continued from previous page

VARIABLES	(1) Consumer Switch	(2) Consumer Switch	(3) Consumer Switch
Malta		0.815*	0.834*
		(0.083)	(0.073)
Netherlands		1.696***	1.661***
		(0.189)	(0.172)
Poland		2.226***	1.890***
		(0.246)	(0.190)
Portugal		2.028***	1.686***
		(0.234)	(0.168)
Romania		2.214***	1.820***
		(0.271)	(0.212)
Sweden		1.870***	1.696***
		(0.221)	(0.200)
Slovenia		1.306*	1.204*
		(0.138)	(0.109)
Slovakia		1.677***	1.486***
		(0.161)	(0.123)
United Kingdom		2.159***	1.992***
		(0.245)	(0.213)
Comparability			
Very difficult			1.138**
			(0.051)
Difficult			1.316***
			(0.039)
Neither difficult or easy			1.139***
			(0.028)
Easy			1.063**
			(0.020)
Very easy			*Ref*
Trust			
Strong mistrust			2.162***
			(0.078)
Mistrust			2.063***
			(0.082)
Neither mistrust or trust			1.764***
			(0.052)
Trust			1.348***
			(0.034)
Strong trust			*Ref*

Continued on next page

Table C.1 – continued from previous page

VARIABLES	(1) Consumer Switch	(2) Consumer Switch	(3) Consumer Switch
Ease of switching			
Very difficult			0.301***
			(0.017)
Difficult			0.360***
			(0.017)
Neither difficult or easy			0.375***
			(0.014)
Easy			0.593***
			(0.012)
Very easy			*Ref*
Lives up to expectation			
Very poor			1.175***
			(0.048)
Poor			1.449***
			(0.056)
Neither poor or well			1.250***
			(0.040)
Well			1.129***
			(0.021)
Very well			*Ref*
Complaints			
None			*Ref*
To a retailer/provider			3.341***
			(0.106)
To an official third party			4.604***
			(0.280)
To friend/family			3.296***
			(0.090)
Constant	0.186***	0.098***	0.082***
	(0.009)	(0.015)	(0.011)
Observations	674,819	674,819	674,819
Wald χ^2 Statistic	589.27	2,424.70	12,192.52

Cluster robust standard errors in parenthesis
***p<0.01, **p<0.05, *p<0.1

Table C.2: Consumer switching logit results (odds ratios) across energy markets weighted by EU27 population with standard errors reported.

VARIABLES	Electricity Consumer Switch	Natural Gas Consumer Switch	Energy Markets† Consumer Switch
Female	0.969	1.025	0.977
	(0.069)	(0.068)	(0.073)
Age			
18-34 years	1.006	0.953	1.028
	(0.057)	(0.098)	(0.079)
35-54 years	*Ref*	*Ref*	*Ref*
55+ years	0.989	0.991	0.950
	(0.087)	(0.119)	(0.084)
Occupation			
Self-employed	1.043	1.041	0.906
	(0.085)	(0.137)	(0.173)
Manager	0.836	1.016	1.030
	(0.115)	(0.125)	(0.170)
White collar	*Ref*	*Ref*	*Ref*
Blue collar	0.938	0.918	0.872**
	(0.058)	(0.057)	(0.039)
Student	0.697*	0.892	0.613
	(0.117)	(0.298)	(0.212)
House-person	0.934	0.823	0.819
	(0.115)	(0.099)	(0.095)
Unemployed	0.984	0.930	1.009
	0.108)	(0.069)	(0.108)
Retired	0.961	0.898	1.028
	(0.074)	(0.144)	(0.095)
Education			
<15 years	0.991	1.026	1.037
	(0.091)	(0.085)	(0.119)
16-19 years	1.011	0.986	1.040
	(0.086)	(0.087)	(0.174)
20+ years	*Ref*	*Ref*	*Ref*
Still studying	1.006	0.935	1.253
	(0.302)	(0.210)	(0.302)
Phone			
Fixed line only	0.781*	1.018	1.001
	(0.082)	(0.151)	(0.168)

Continued on next page

Table C.2 – continued from previous page

VARIABLES	Electricity Consumer Switch	Natural Gas Consumer Switch	Energy Markets† Consumer Switch
Mobile only	0.918	1.032	0.942
	(0.067)	(0.090)	(0.059)
Mixed	*Ref*	*Ref*	*Ref*
Internet			
Internet usage	*Ref*	*Ref*	*Ref*
No internet usage	0.708***	0.742***	0.754***
	(0.049)	(0.041)	(0.047)
Year			
2010	*Ref*	*Ref*	*Ref*
2011	1.183	1.093	1.179
	(0.087)	(0.147)	(0.171)
2012	0.962	0.821	0.994
	(0.163)	(0.156)	(0.110)
2013	0.860	0.884	0.971
	(0.165)	(0.167)	(0.118)
Market			
Electricity			*Ref*
Gas			0.961
			(0.093)
Country			
Germany	*Ref*	*Ref*	*Ref*
Austria	0.679***	0.594***	0.695***
	(0.036)	(0.019)	(0.037)
Belgium	1.684***	1.954***	2.207***
	(0.081)	(0.056)	(0.090)
Bulgaria	0.051***	1.887***	0.876
	(0.011)	(0.070)	(0.076)
Cyprus	-	-	-
	-	-	-
Czech Republic	1.018	1.506***	1.400***
	(0.080)	(0.099)	(0.080)
Ireland	1.969***	1.655***	1.944***
	(0.059)	(0.050)	(0.050)
Denmark	1.162***	0.733***	0.993
	(0.050)	(0.030)	(0.062)

Continued on next page

Table C.2 – continued from previous page

VARIABLES	Electricity Consumer Switch	Natural Gas Consumer Switch	Energy Markets† Consumer Switch
Estonia	2.104***	0.459***	1.079
	(0.141)	(0.013)	(0.044)
Greece	-	0.452***	0.114***
	-	(0.010)	(0.004)
Spain	0.876	1.065	0.909
	(0.128)	(0.056)	(0.087)
Finland	1.562***	0.434***	1.556***
	(0.079)	(0.042)	(0.085)
France	0.609***	0.782***	0.716***
	(0.020)	(0.033)	(0.035)
Hungary	0.170***	0.869	0.606**
	(0.026)	(0.078)	(0.092)
Italy	1.474***	0.915	1.149
	(0.143)	(0.067)	(0.103)
Lithuania	1.226*	-	1.142
	(0.103)		(0.141)
Luxembourg	0.440***	0.571***	0.428***
	(0.006)	(0.020)	(0.027)
Latvia	0.409***	0.635***	0.553***
	(0.054)	(0.019)	(0.042)
Malta	-	-	-
	-	-	-
Netherlands	1.894***	1.660***	1.618***
	(0.030)	(0.078)	(0.112)
Poland	0.654***	0.617***	0.695***
	(0.054)	(0.012)	(0.045)
Portugal	0.999	0.754***	0.707**
	(0.117)	(0.029)	(0.087)
Romania	0.546***	0.624***	0.509***
	(0.052)	(0.020)	(0.055)
Sweden	1.672***	1.079	1.864***
	(0.135)	(0.127)	(0.132)
Slovenia	0.610***	0.794***	0.760***
	(0.023)	(0.031)	(0.030)
Slovakia	0.863**	1.643***	1.271***
	(0.049)	(0.196)	(0.039)
United Kingdom	1.375***	1.535***	1.510***
	(0.107)	(0.071)	(0.094)
Comparability			
Very difficult	0.858	1.209*	1.140
	(0.071)	(0.114)	(0.144)
Difficult	1.308***	1.517***	1.186*
	(0.069)	(0.172)	(0.082)

Continued on next page

Table C.2 – continued from previous page

VARIABLES	Electricity Consumer Switch	Natural Gas Consumer Switch	Energy Markets† Consumer Switch
Neither difficult or easy	1.097	1.274**	1.096
	(0.082)	(0.109)	(0.108)
Easy	1.088	1.113	1.069
	(0.073)	(0.095)	(0.099)
Very easy	*Ref*	*Ref*	*Ref*
Trust			
Strong mistrust	2.658***	2.441***	2.759***
	(0.360)	(0.289)	(0.259)
Mistrust	2.186***	2.253***	2.382***
	(0.344)	(0.413)	(0.372)
Neither mistrust or trust	2.071***	1.990***	2.179***
	(0.216)	(0.197)	(0.231)
Trust	1.534***	1.532***	1.768***
	(0.120)	(0.169)	(0.271)
Strong trust	*Ref*	*Ref*	*Ref*
Ease of switching			
Very difficult	0.218***	0.194***	0.179***
	(0.030)	(0.021)	(0.023)
Difficult	0.219***	0.260***	0.269***
	(0.043)	(0.060)	(0.064)
Neither difficult or easy	0.254***	0.297***	0.279***
	(0.024)	(0.049)	(0.046)
Easy	0.490***	0.554***	0.495***
	(0.031)	(0.026)	(0.026)
Very easy	*Ref*	*Ref*	*Ref*
Lives up to expectation			
Very poor	1.526*	1.438*	1.194
	(0.316)	(0.230)	(0.111)
Poor	1.924***	1.471*	1.778**
	(0.227)	(0.225)	(0.327)
Neither poor or well	1.522**	1.224	1.204
	(0.240)	(0.155)	(0.120)
Well	1.186***	1.117*	1.136*
	(0.056)	(0.051)	(0.067)
Very well	*Ref*	*Ref*	

Continued on next page

Table C.2 – continued from previous page

VARIABLES	Electricity Consumer Switch	Natural Gas Consumer Switch	Energy Markets† Consumer Switch
Complaints			
None	*Ref*	*Ref*	*Ref*
To a retailer/provider	3.700***	4.238***	4.714***
	(0.547)	(0.569)	(0.705)
To an official third party	6.197***	5.551***	6.361***
	(1.913)	(1.747)	(1.965)
To friend/family	2.698***	3.876***	3.646***
	(0.534)	(0.411)	(0.236)
Other non-energy switches			
None			*Ref*
At least one other switch			2.328***
			(0.416)
Constant	0.119***	0.102***	0.074***
	(0.015)	(0.012)	(0.013)
Observations	45,026	43,241	43,648
Log Likelihood	-1.7e+04	-1.5e+04	-1.5e+04

† Sub-sample of energy consumers surveyed on three or more switching markets
Cluster robust standard errors in parenthesis
***p<0.01, **p<0.05, *p<0.1

Table C.3: Consumer switching logit results (odds ratios) by country with standard errors reported.

VARIABLES	Ireland Consumer Switch	United Kingdom Consumer Switch	Germany Consumer Switch	Denmark Consumer Switch	Spain Consumer Switch	France Consumer Switch	Lithuania Consumer Switch
Female	0.898***	1.024	0.975	1.071	0.977	1.039	0.983
	((0.026)	(0.040)	(0.057)	(0.046)	(0.023)	(0.042)	(0.049)
Age							
18-34 years	1.106	1.186**	0.989	1.349***	1.094	0.990	1.221**
	(0.101)	(0.069)	(0.094)	(0.078)	(0.087)	(0.076)	(0.076)
35-54 years	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
55+ years	0.748***	0.836*	1.032	0.895	0.871***	0.825***	1.075
	(0.034)	(0.063)	(0.058)	(0.060)	(0.033)	(0.046)	(0.072)
Occupation							
Self-employed	1.182	0.982	0.911	1.388***	1.209***	1.280**	1.120
	(0.107)	(0.067)	(0.065)	(0.118)	(0.052)	(0.105)	(0.080)
Manager	1.148*	1.049	0.928	1.085	1.170*	1.063	1.073
	(0.066)	(0.064)	(0.077)	(0.080)	(0.080)	(0.082)	(0.079)
White collar	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
Blue collar	0.943	0.938	0.901	1.006	1.040	0.891	0.927
	(0.049)	(0.064)	(0.074)	(0.047)	(0.053)	(0.090)	(0.062)
Student	0.891	0.942	0.839	1.313**	0.997	1.291	0.837
	(0.102)	(0.209)	(0.148)	(0.134)	(0.131)	(0.394)	(0.082)
House-person	0.915	0.930	0.656***	0.854	0.897	0.853	0.947
	(0.087)	(0.065)	(0.077)	(0.130)	(0.051)	(0.090)	(0.040)
Unemployed	0.823*	0.789***	0.810*	1.139	1.130*	1.107	0.803**
	(0.078)	(0.037)	(0.067)	(0.096)	(0.068)	(0.185)	(0.066)
Retired	0.965	1.021	0.679***	0.964	0.983	0.833	0.990
	(0.053)	(0.072)	(0.051)	(0.063)	(0.069)	(0.090)	(0.085)
Education							
<15 years	0.949	0.906**	1.127	0.821**	0.923*	1.151	0.834***
	(0.053)	(0.032)	(0.117)	(0.051)	(0.037)	(0.096)	(0.027)
16-19 years	0.836***	0.968	1.108	0.864**	0.939	1.027	0.925
	(0.032)	(0.049)	(0.065)	(0.040)	(0.036)	(0.053)	(0.073)
20+ years	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
Still studying	1.047	1.094	0.980	0.872	0.889	0.646	0.958
	(0.117)	(0.159)	(0.212)	(0.108)	(0.126)	(0.197)	(0.127)

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Table C.3 – continued from previous page

VARIABLES	Ireland Consumer Switch	United Kingdom Consumer Switch	Germany Consumer Switch	Denmark Consumer Switch	Spain Consumer Switch	France Consumer Switch	Lithuania Consumer Switch
Phone							
Fixed line only	0.839	0.803*	1.242	0.700	0.828*	0.996	0.908
	(0.110)	(0.084)	(0.158)	(0.128)	(0.077)	(0.134)	(0.122)
Mobile only	1.054	0.819***	0.808*	1.073	1.031	1.177	1.025
	(0.079)	(0.031)	(0.087)	(0.069)	(0.077)	(0.145)	(0.040)
Mixed	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
Internet							
Internet usage	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
No internet usage	0.702***	0.725***	0.670***	0.605***	0.682***	0.663**	0.703***
	(0.039)	(0.064)	(0.043)	(0.053)	(0.036)	(0.086)	(0.036)
Year							
2010	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
2011	1.193	0.990	1.207*	1.305**	1.032	1.151	0.953
	(0.136)	(0.088)	(0.108)	(0.110)	(0.084)	(0.123)	(0.074)
2012	1.131	1.136	0.504***	0.896	1.187	0.718**	1.014
	(0.088)	(0.089)	(0.033)	(0.103)	(0.135)	(0.074)	(0.084)
2013	1.068	1.105	0.406***	1.006	1.181	0.882	1.044
	(0.090)	(0.071)	(0.036)	(0.085)	(0.159)	(0.083)	(0.113)
Market							
Electricity	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
Bank accounts	0.439***	0.768***	0.610***	1.102***	1.504***	1.282***	1.649***
	(0.015)	(0.017)	(0.008)	(0.020)	(0.031)	(0.020)	(0.147)
Loans and credit	0.498***	1.117***	0.575***	1.423***	1.547***	1.415***	1.289***
	(0.012)	(0.025)	(0.009)	(0.018)	(0.023)	(0.019)	(0.085)
Investment products	1.180***	1.756***	0.830***	1.935***	2.654***	1.377***	2.224***
	(0.040)	(0.035)	(0.020)	(0.041)	(0.067)	(0.026)	(0.152)
Home insurance	1.076***	1.285***	0.590***	1.008	1.182***	1.084***	1.059
	(0.020)	(0.024)	(0.012)	(0.026)	(0.038)	(0.016)	(0.080)
Vehicle insurance	1.094***	1.765***	0.994	1.167***	1.702***	1.260***	3.045***
	(0.015)	(0.030)	(0.009)	(0.030)	(0.055)	(0.014)	(0.248)
Fixed telephone	0.734***	0.866***	0.709***	1.374***	2.504***	1.648***	3.821***
	(0.013)	(0.011)	(0.012)	(0.033)	(0.065)	(0.023)	(0.287)
Mobile telephone	0.661***	1.010	1.078***	5.587***	3.217***	2.382***	4.599***
	(0.013)	(0.015)	(0.010)	(0.130)	(0.055)	(0.025)	(0.375)
Internet	0.763***	0.887***	0.713***	1.504***	2.663***	1.478***	2.773***
	(0.015)	(0.022)	(0.016)	(0.040)	(0.050)	(0.031)	(0.213)

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Table C.3 – continued from previous page

VARIABLES	Ireland Consumer Switch	United Kingdom Consumer Switch	Germany Consumer Switch	Denmark Consumer Switch	Spain Consumer Switch	France Consumer Switch	Lithuania Consumer Switch
Commercial sport	0.709***	0.921*	0.671***	1.194***	1.618***	1.340***	2.168***
	(0.015)	(0.033)	(0.009)	(0.044)	(0.063)	(0.032)	(0.207)
Gas	0.776***	1.075***	0.839***	0.594***	1.169***	1.230***	-
	(0.006)	(0.006)	(0.010)	(0.007)	(0.020)	(0.011)	-
Mortgages	0.237***	1.312***	0.668***	2.684***	0.442***	0.952	0.940
	(0.015)	(0.049)	(0.028)	(0.096)	(0.023)	(0.033)	(0.047)
Private life insurance	0.624***	0.767***	0.584***	1.165***	1.313***	1.197***	1.238**
	(0.022)	(0.023)	(0.023)	(0.036)	(0.048)	(0.031)	(0.089)
TV subscriptions	0.622***	0.764***	0.448***	2.033***	1.127***	1.194***	1.814***
	(0.019)	(0.025)	(0.016)	(0.064)	(0.037)	(0.037)	(0.146)
Comparability							
Very difficult	1.331***	0.944	1.531***	1.456***	0.931	0.988	1.205*
	(0.108)	(0.147)	(0.193)	(0.147)	(0.090)	(0.151)	(0.107)
Difficult	1.257*	1.235*	1.364**	1.483***	1.097	1.034	1.483***
	(0.115)	(0.102)	(0.148)	(0.114)	(0.071)	(0.095)	(0.128)
Neither	1.063	0.923	1.395***	1.190**	1.050	1.167*	1.276***
	(0.059)	(0.041)	(0.112)	(0.067)	(0.033)	(0.085)	(0.086)
Easy	1.097	1.036	1.080	1.295***	0.947	0.990	1.154**
	(0.055)	(0.043)	(0.070)	(0.059)	(0.039)	(0.072)	(0.058)
Very easy	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
Trust							
Strong mistrust	2.289***	2.306***	2.107***	1.462**	2.147***	3.106***	1.491**
	(0.298)	(0.195)	(0.251)	(0.202)	(0.162)	(0.373)	(0.193)
Mistrust	2.154***	2.071***	2.091***	1.278*	1.909***	2.563***	1.552***
	(0.257)	(0.264)	(0.264)	(0.153)	(0.227)	(0.386)	(0.086)
Neither	1.727***	1.846***	1.940***	1.036	1.648***	2.225***	1.268***
	(0.122)	(0.115)	(0.127)	(0.089)	(0.112)	(0.296)	(0.088)
Trust	1.269***	1.405***	1.486***	0.990	1.247**	1.428**	1.187**
	(0.048)	(0.098)	(0.074)	(0.064)	(0.091)	(0.178)	(0.069)
Strong trust	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
Ease of switching							
Very difficult	0.209***	0.265***	0.414***	0.211***	0.339***	0.553***	0.467***
	(0.036)	(0.028)	(0.063)	(0.046)	(0.058)	(0.081)	(0.078)
Difficult	0.299***	0.300***	0.421***	0.307***	0.379***	0.610***	0.419***
	(0.054)	(0.038)	(0.083)	(0.042)	(0.043)	(0.069)	(0.067)
Neither	0.381***	0.311***	0.575***	0.160***	0.486***	0.567***	0.496***
	(0.047)	(0.021)	(0.066)	(0.016)	(0.039)	(0.063)	(0.064)

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Table C.3 – continued from previous page

VARIABLES	Ireland Consumer Switch	United Kingdom Consumer Switch	Germany Consumer Switch	Denmark Consumer Switch	Spain Consumer Switch	France Consumer Switch	Lithuania Consumer Switch
Easy	0.551***	0.527***	0.636***	0.516***	0.725***	0.663***	0.695***
	(0.042)	(0.022)	(0.042)	(0.036)	(0.032)	(0.054)	(0.051)
Very easy	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
Expectation							
Very poor	0.898	1.090	2.018***	1.847***	1.090	1.151	1.043
	(0.098)	(0.132)	(0.277)	(0.208)	(0.088)	(0.229)	(0.115)
Poor	1.034	1.212	2.071***	1.927***	1.285**	1.810***	1.295***
	(0.120)	(0.186)	(0.272)	(0.352)	(0.116)	(0.196)	(0.097)
Neither	0.913	0.941	1.971***	1.465***	1.002	1.621***	1.229**
	(0.064)	(0.045)	(0.150)	(0.104)	(0.046)	(0.181)	(0.093)
Well	1.032	1.107	1.259***	1.310***	1.028	1.170*	1.219**
	(0.046)	(0.058)	(0.076)	(0.069)	(0.057)	(0.084)	(0.082)
Very well	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
Complaints							
None	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
To a retailer/provider	2.638***	2.824***	4.661***	2.199***	3.110***	4.311***	2.171***
	(0.186)	(0.170)	(0.560)	(0.141)	(0.184)	(0.367)	(0.229)
To an official third party	3.033***	3.467***	8.670***	1.783**	4.225***	4.623***	2.087***
	(0.582)	(0.732)	(2.291)	(0.397)	(0.196)	(1.120)	(0.419)
To friend/family	3.427***	3.486***	3.860***	2.312***	3.327***	4.331***	2.360***
	(0.288)	(0.180)	(0.421)	(0.247)	(0.217)	(0.597)	(0.221)
Constant	0.298***	0.213***	0.103***	0.180***	0.106***	0.043***	0.105***
	(0.019)	(0.019)	(0.009)	(0.019)	(0.013)	(0.006)	(0.016)
Observations	27,290	27,263	27,074	27,113	26,874	27,251	23,331
Log Likelihood	-2620.59	-3.8e+04	-3.5e+04	-3224.10	-2.8e+04	-2.5e+04	-1917.36

Cluster robust standard errors in parenthesis
***p<0.01, **p<0.05, *p<0.1