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The Role of Information in Household Energy Decisions

Submitted to the University of Dublin, Trinity College, in application for the degree of Doctor of Philosophy (Economics)

James Carroll

Supervised by Dr. Eleanor Denny and Dr. Seán Lyons

August, 2014

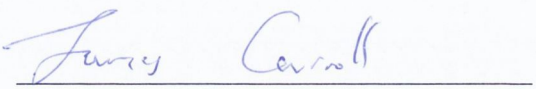
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Summary

This dissertation explores the effects of various informational policy interventions in a number of energy markets. Using a number of trials and surveys, this research aims to highlight a household's underlying energy-reducing motivations, the presence of market failures related to imperfect or asymmetric information and the effect and justification for informational policy intervention. Chapter 1 introduces this dissertation, discusses the specific research questions explored and provides a brief description of the background to energy-related research of this kind (climate change).

Chapter 2 uses data from a recent smart metering trial to explore the existence of imperfect information in residential electricity markets. While previous research has found that feedback has led to reductions in demand, this paper explores the role of knowledge improvements within this process. The results show that households did improve their self-reported level of knowledge related to energy-saving behaviours and appliance consumption levels. However, improvements in knowledge play no role in the observed demand reductions during the year-long trial. This finding brings into question the 'imperfect information' rationale for feedback intervention. It is possible that households reduced their demand because more detailed, accurate and informative feedback increased the number of reminders and therefore the motivation to reduce.

The energy efficiency gap describes the aggregate failure of households to invest in more energy efficient technologies, despite the fact that they often represent the cost-minimising alternative over the life of the product. Chapter 3 discusses a number of reasons why this may be the case, including imperfect information, uncertainty, loss aversion and status-quo bias. The paper tests one potential behavioural failure – that buyers are either inattentive to (or are unable to calculate) the total costs of their energy-consuming products. This is tested by adding a 'lifetime' consumption cost label to the entire tumble dryer lineup in four stores of an Irish retailer. Results show that sales are positively influenced by appliance features, such as capacity and timers, and negatively affected by price. While efficiency improved in treatment stores, this positive effect is not statistically significant.

Chapter 4 explores the role of asymmetric information in property rental markets. Rental properties have significantly lower levels of energy efficiency than owner-occupied. Asymmetric information in relation to a property's energy attributes helps explain this owner-renter efficiency divide as it depicts a market with uncertain quality for buyers, or an equivalent rental market 'lemons' problem - as renters cannot differentiate between high and low efficiency (without cost) they will assume an average, and landlords, knowing that energy efficiency is not rewarded through higher rents, have no incentive to invest. Independent energy ratings, although a seemingly straightforward solution to the problem, rest upon one important assumption – that the willingness-to-pay for energy efficiency in a perfectly informed rental market covers the cost of capital (for landlords). This paper uses a discrete choice experiment which asks renters to choose from a hypothetical set of single-bedroom apartments which differ according to a number of attributes, including energy efficiency. Results show that renters will pay more for higher energy efficiency but that the marginal increase in rents is likely below the cost of capital, on average. It is therefore unlikely that removing the informational asymmetry will promote considerable energy efficiency investment.

Chapter 5 concludes the dissertation and returns to the overall discussion on climate change. Limitations of the research are highlighted and a number of promising areas for future research are outlined. Furthermore, future global greenhouse gas (GHG) abatement targets are discussed in light of the large and consistent emission increases over the last 20 years. While informational policies will play a role in reducing household demand, the magnitude of the specific policies observed in this thesis suggest that, currently, their role will be a minor one (given prevailing energy prices and household tastes and preferences).

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Publications and Conference Papers

Publications:

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- ENERDAY 2014, Dresden: April 2014

- Irish Economic Association, Limerick, Ireland: May 2014

- International Energy Workshop, Beijing: June 2014

CARROLL, J., LYONS, S. & DENNY, E. 2013. Reducing Electricity Demand through Smart Metering: The Role of Improved Household Knowledge:

Presented at:

- Young Energy Economists and Engineers Seminar, Vienna: March 2013 (awarded joint second best paper)

- Irish Economic Association, Maynooth, Ireland: May 2013

- ERC Research Symposium, UCD, Ireland: May 2013

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Chapter 1

Introduction

1.1 Thesis and Chapter Overview

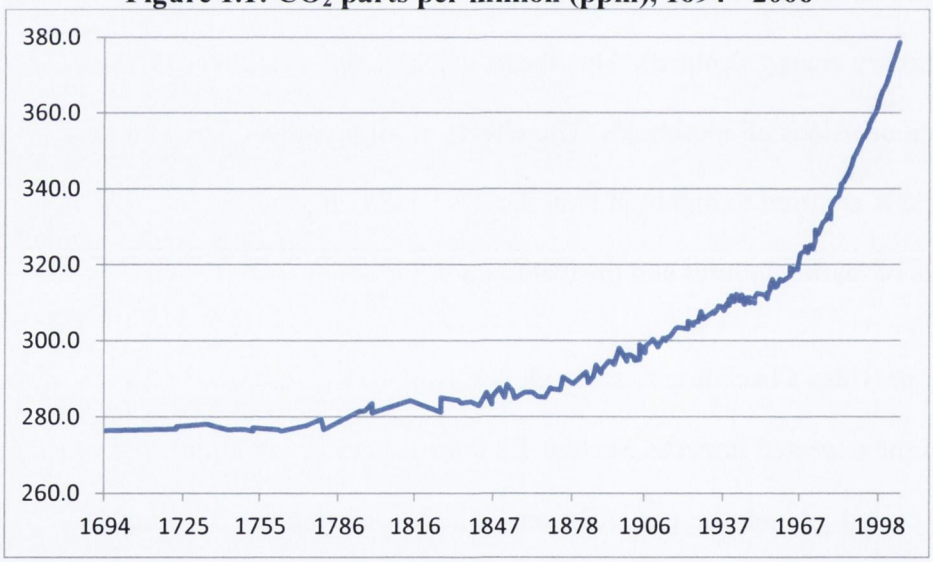
The residential sector is the second highest energy consumer in Ireland, with 27% of primary energy demand and 34% of electricity demand (SEAI, 2013). Households also consume about half of all energy used in transport, the highest consuming sector in Ireland (32% of primary energy demand). This thesis explores the energy-related investment and consumption decisions of households. The effects of informational interventions in various energy markets are used to highlight household's underlying energy-reducing motivations, the presence of market failures and the justification for policy intervention.

Section 1.2 provides a backdrop to research in this field, with a brief description of climate change and the expected impacts. Section 1.3 discusses the international policies currently in place to curtail greenhouse gas emissions, with a focus on specific supply and demand policies in Ireland and the EU. Section 1.4 discusses the main information-related market failures discussed in this thesis and provides a motivation for analysis of later chapters.

1.2 Climate Change: Description and Impact

It is difficult to overemphasise the recent and significant deviations from long-run climatic trends, nor the negative effects of higher global temperatures. Ice core analyses show that the concentration of atmospheric CO_2 has broadly fluctuated between 180 and 280 parts per million (ppm) for at least 800,000 years (Luthi et al., 2008). Increased combustion of fossil fuels since the start of the industrial revolution has, however, led to unprecedented rates of increase, particularly since the 1950s (Figure 1.1) (MacFarling Meure et al., 2006). By April of this year, the mean monthly CO_2 level at the Mauna Lao Observatory, Hawaii, exceeded a symbolic milestone of 400 ppm, the highest level since records began in 1959, and likely in the last million years.[1]

Figure 1.1: CO_2 parts per million (ppm), 1694 - 2006



Note: Data from MacFarling Meure et al. (2006) downloaded from http://hurricane.ncdc.noaa.gov/pls/paleox/f?p=519:1:::::P1_STUDY_ID:9959

CO_2 is the main greenhouse gas (GHG) contributing to climate change (in addition to methane, nitrous oxide and chlorofluorocarbons (Lashof and Ahuja, 1990)) and, in the long-term, periods of increased CO_2 show increases in temperature (Luthi et al., 2008).

[1] www.esrl.noaa.gov/gmd/ccgg/trends/index.html

Furthermore, much of these increases are absorbed and stored in the earth's oceans, making climate change largely irreversible in periods of less than 1000 years (Solomon et al., 2009). The recent Intergovernmental Panel on Climate Change (IPCC) reports show that global surface temperatures have increased by 0.85 degrees Celsius since 1880, and that the last three decades have been warmer than any other since 1850. Ocean temperatures have also been warming by 0.11 degrees per decade since 1970. Visible and scientifically documented impacts of rising temperatures are shrinking glaciers, declining snow coverage, increased ice loss from the Greenland and Antarctic ice sheets, and declines in Arctic and Antarctic sea ice extent, all of which have led to increased sea levels. It is also 'likely' that there has been increased numbers of warm days, heat waves and heavy precipitation events since the 1950s (IPCC, 2013).

Over the 21st century, climate change will have severe negative impacts on ecosystems, livelihoods and human health (IPCC, 2014b). High temperatures and drought will degrade terrestrial and freshwater ecosystems, raising the risk of species extinction and forest dieback. Ocean acidification due to carbon absorption poses particular threats to polar ecosystem and coral reef survival. In urban areas, there will be increased heat stress, extreme participation, landslides, and periods of drought and water security. Low-lying areas and coastal systems will increasingly experience submergence, flooding and erosion, with dramatic effects on coastal ecosystems and livelihoods. Furthermore, the majority of the above is more acute in tropical regions, where current low living standards and resources will exacerbate the negative effects and limit adaptability (IPCC, 2014b). The severity of these impacts is proportionate to the rate of CO_2 mitigation by nations in the coming century, with the next 30 years critical for alleviating the most damaging long-run effects. The most optimistic climate scenario (IPCC, 2014a) suggests that atmospheric CO_2 concentrations will need to be around 450 ppm by 2100 in order to keep temperatures to

less than 2 degrees Celsius above pre-industrial levels. In order to achieve this, GHG emissions in 2050 will need to be 40-70% lower than today's, and close to zero by 2100.

1.3 Policy Response – Ireland and the EU

1.3.1 International Context

The United Nations Framework Convention on Climate Change (UNFCCC) was established in 1994 and is the only coordinated international treaty to stabilise global GHG emissions. The Kyoto Protocol (1997), which set emissions targets for developed countries (including all 'EU' countries), came into force in 2005. During the first commitment period (2008 – 2012), an average GHG reduction of five percent compared to 1990 levels was required, with different targets for each country. The second commitment period (2013 – 2020) increased average emissions cuts to 18 percent. Within the treaty, the EU maintained an overall target but allowed individual member states to deviate according to size and level of economic development. For the current period, the EU has committed to overall reductions of 20% by 2020.

1.3.2 Supply Policies

SEAI (2013) provide a summary of the EU's main GHG reduction policies and Ireland's current obligations and individual policies. The cornerstone of the EU's GHG policies is the *Emissions Trading System* (ETS), which grants polluters (power stations, industry and airlines) emission allowances (each allowing one tonne of CO_2 emissions, or other GHG equivalent) which can be traded on the open market (European Commission, 2013). The number of allowances (and therefore aggregate emissions) is reduced by 1.74% each year

to ensure a 20% reduction by 2020 and the system currently covers 45% of the EU's GHG emissions. The policy increases the relative profitability of more efficient generators and manufacturers and carbon prices should provide the market conditions which will promote more energy efficient investments. Ireland, under Directive 2009/29/EC, is required to reduce the emissions of ETS companies to 21% below 2005 levels by 2020 (European Commission, 2009d).

The EU also regulates the technical specification of energy-consuming products. For example, Regulation 443/2009 sets efficiency standards for cars, and aims to reduce the average fleet consumption of new vehicles to 130 grams of CO_2 per kilometer by 2015 (159 in 2007) and then to 95 by 2020 (European Commission, 2009e). This is achieved by imposing and gradually reducing upper emission limits (by weight category) for EU car manufacturers (a similar policy is currently in place for light commercial vehicles and regulations for trucks, buses and coaches is currently being established). For the majority of other energy consuming products, specific EU 'eco-design' legislation impose energy efficiency standards on manufacturers which are again continually updated and tightened (for example, see European Commission (2009a) for current television regulations). Eco-designs regulations are currently in place for cookers, refrigerators, freezers, tumble dryers, televisions, electric motors, washing machines, dishwashers, heaters (space and hot water), vacuum cleaners, water pumps, air conditioning units and set-top boxes.

Under Decision 406/2009/EC, Ireland's non-ETS emissions must be reduced by 20% (European Commission, 2009b), and under Directive 2009/28/EC, there is a 10% renewable target for both gross final energy consumption and transport (European Commission, 2009c). In meeting its renewable and non-ETS targets, Irish governments have applied a number of national policies. To encourage renewable electricity generation investment, the *Renewable Energy Feed in Tariff* (REFIT) was launched in 2009. The

current scheme guarantees wholesale energy prices for a number of renewable generation technologies, including wind, biomass, hydro and combined heat and power. Off-shore renewables (wind, wave and tidal) are also likely to receive similar support in the coming decade (Department of Communications Energy and Natural Resources, 2014). In transport, a biofuels obligation came into effect in 2010, which ensures that a percentage (currently 6.4%) of petroleum-based motor fuels come from biofuels (Government of Ireland, 2012). Also, Irish building regulations (Part L) impose that a renewable energy source is required for electricity and/or water/space heating in new residential buildings (Government of Ireland, 2011). These regulations also impose minimum standards for boiler efficiency, insulation and heating (space and water) controls.

1.3.3 Demand policies – grants and taxes

The above policies either reduce the supply of inefficient products through regulation (imposing minimum standards for appliances, cars and buildings) or promote investment in cleaner generation technologies by increasing the cost of polluting (ETS). Both will likely lower energy consumption – the former will improve the energy efficiency of the economy's technology stock thus lowering the number of energy units consumed, while the latter will likely put upward pressure on electricity prices due to increased production costs. Demand reducing policies, on the other hand, aim to influence end-user energy efficiency investments or consumption behaviours, and include subsidies, taxation and information.

The Sustainable Energy Authority of Ireland (SEAI) administers a number of efficient technology supports for households (under the 'Better Energy Homes' scheme) and grants are currently available for roof and wall insulation, boiler and heating controls, solar panels

(hot water) and electric vehicles.[2] There are also a number of taxation changes which promote more efficient technology investment and use. In 2008, Irish vehicle taxation (initial vehicle registration and annual taxation payments) switched to a carbon-based system (previously based on engine size). Furthermore, the Finance Act 2010 (Government of Ireland, 2009) introduced a carbon tax on petrol and diesel in December 2009 which was later extended to other mineral oils and natural gas in May 2010 and solid fuels in May 2013 (current price is €20 per tonne of CO_2 emitted, as of May 2014).

1.3.4 Demand policies – energy information for households

There are numerous examples of government schemes designed to improve household energy information, whether for increasing understanding of appliance consumption levels, directing household investment towards higher efficiency or changing general energy behaviours. Between September 2006 and March 2008, the Irish government conducted a nationwide energy efficiency campaign ('The Power of One'). This used a number of media alternatives (television, radio, internet, newspapers, billboards and leaflets accompanying utility bills) and provided households with information and advice on improving mileage and appliance purchases and reducing peak electricity usage, home heating and electricity consumption (Diffney et al., 2009).

Smart metering is another way to inform households about their energy usage. Through more detailed billing and/or an in-house display, households can receive more accurate information on which appliances and behaviours consume the most. This new information may also inform future appliance purchasing decisions. In Ireland, an electricity and gas smart meter trial (5000 households) was undertaken between 2009 and 2010 by the Commission for Energy Regulation (CER, 2011c). The trial simultaneously applied

[2] Information on SEAI and their supports is available from www.seai.ie

various levels of feedback and time-of-use tariffs and found significant peak and overall reductions of 8.8% and 2.5% respectively. A national roll-out of gas and electricity smart meters is expected in 2015 (CER, 2012).

EU-wide energy efficiency labelling of appliances covers the main household energy-consuming products (tumble dryers, washing machines, fridges, freezers, air conditioners, dishwashers and lights). Appliances are categorised using a colour-coded efficiency band system. Directive 1999/94/EC describes a similar system for cars, where information on fuel economy and CO_2 emissions is provided at the point of sale (European Commission, 1999). The EU also requires, under Directive 2002/91/EC, that member states provide energy efficiency information for buildings at the point of sale or lease (European Commission, 2002). In Ireland, this led to the Building Energy Rating (BER) certification system in 2009. The BER combines all of a property's efficiency attributes (including space/water heating, insulation, ventilation and lighting) into a single figure (kWh/m^2/annum), again presented on a colour-coded categorical scale. Certification is carried out by registered, independent and state-monitored BER assessors. Furthermore, as of 2013, all property advertisements, for sale or lease, must now also include the BER rating (European Commission, 2010b).

1.4 Thesis Motivation and Overview

1.4.1 Market failure and the economics of energy consumption

Although there are a wide range of policy options available for reducing household energy demand, this dissertation focuses on a number of specific informational interventions which are designed to reduce energy demand or promote more energy-saving investments. The effects of three specific informational interventions – smart metering, appliance

labelling and property labelling – are used to explore a household's underlying energy-reducing motivations and the existence of various market failures in electricity, appliance and rental (property) markets.

Contemporary energy-saving technologies, from electric cars to solar heating systems to A-rated appliances, generally involve an increased investment cost (relative to the status quo technology) in exchange for decreased future energy expenditure, *ceteris paribus*. The failure to choose more efficient energy-consuming products, not only increases energy demand, generation and environmental damage, but often represents a deviation from cost-minimising behaviour and therefore has a negative impact on private welfare. On aggregate, this has become known as the 'energy efficiency gap' (Jaffe and Stavins, 1994a).

There are a number of theories which help explain this misoptimisation. A standard market failure discussed by Jaffe and Stavins (1994b) relates to the availability of auxiliary cost information. Imperfect information, on a fundamental level, implies that buyers are simply unaware of their current efficiency level or, more importantly, the costs and benefits of contemporary technologies. It is therefore not surprising that much public policy to date has attempted to remove this market failure through independent appliance consumption labelling. For example, the European Commission (2010a) highlight that efficiency labels are intended to '*influence the end-user's choice in favour of those products which consume or indirectly result in consuming less energy and other essential resources during use.... It should also, indirectly, encourage the efficient use of these products...*' They further state that '*in the absence of this information, the operation of market forces alone will fail to promote the rational use of energy and other essential resources for these products*' (Directive 2010/30/EU, pg. 2).

Asymmetric information related to energy efficiency can also lead to market failures. For example, in property rental markets, some energy-related technologies, such as wall and attic insulation, are unobservable to prospective tenants, and this information is costly to acquire (hiring an independent assessor, for example) (see, for example, Jaffe and Stavins (1994b), Murtishaw and Sathaye (2006), IEA (2007), Davis (2012) and Allcott and Greenstone (2012)). As is the usual outcome in any market with uncertain quality (Akerlof, 1970), there is adverse selection and the market can fail – tenants will assume an average efficiency level and will fail to choose properties which minimize their energy costs, and landlords, knowing that increases in efficiency are not rewarded by increased rents, will have no incentive to invest.

There are also a number of theories from the behavioural economics literature which can be applied to understanding the underutilisation of energy-saving technologies. Firstly, experimental studies support the existence of hyperbolic discounting leading to 'present bias' or 'time-inconsistency' in decision making (Loewenstein and Prelec, 1992, Frederick et al., 2002, Laibson, 1997). This has obvious implications for energy efficiency investment, which, as stated, nearly always involves trading increased immediate costs for future savings.

Furthermore, the decision to buy this new technology represents a choice under uncertainty. In this regard, 'Prospect Theory' (Kahneman and Tversky, 1979, Kahneman and Tversky, 1984, Tversky and Kahneman, 1986) shows that the value change associated with a loss is significantly higher than that for an equivalent gain ('loss aversion'), that choices are driven by context (framing effects) and that decision-makers overweigh certain outcomes (certainty effect). The theory helps explain why decision-makers can often favour an actuarially unfavourable alternative and are reluctant to deviate from their status quo (status quo bias) (Samuelson and Zeckhauser, 1988). For the potential adopter, this

new energy-saving device could be viewed either as an uncertain gain (the energy savings) or as an uncertain loss (this newer untested technology fails) relative to the status quo (the existing inefficient technology, assumed to be a sure bet). Prospect theory tells us that buyers will undervalue uncertain gains and overvalue the uncertain losses higher than their respective risks warrant under rational decision making, which in both cases reduce the attractiveness of an efficiency upgrade in favour of the status quo.

1.4.2 Paper 1 – research question and preview

Paper 1 (Chapter 2) explores the effects of consumption feedback provided through smart meters and questions the presence of imperfect information pre-metering in residential electricity markets. Improved consumption feedback, and in particular, the installation of in-house displays, has been shown to significantly reduce residential electricity demand in most international trials. Data from a recent randomised-controlled smart metring trial in Ireland is used to uncover the underlying drivers of such information-led reductions. The paper explores two research questions: First, does feedback improve a household's stock of information about potential energy reducing behaviours? Second, do improvements in such information explain demand reductions? Although households increased their self-reported stock of energy-reducing information, such improvements are not correlated with the significant demand reductions observed during the trial. This result suggests that reducing the independent imperfect information problem (that is, improving household knowledge of how to reduce energy), is, in the short-run, unlikely to reduce electricity demand. Why households actually reduced their electricity demand is discussed but left to future research. For example, it is possible that feedback and advice changes energy consumption patterns as it acts more as a reminder and motivator. This paper is published in *Energy Economics*, volume 45 (Carroll et al., 2014).

1.4.3 Paper 2 – research question and preview

Paper 2 (Chapter 3) discusses a number of reasons as to why households may fail to choose appliances that minimise their energy costs (the energy efficiency gap). Based on the findings of previous research, it is hypothesised that specific monetary energy cost information is missing from the investment decision. The research question therefore asks – is imperfect information in relation to future energy costs of appliances reducing the demand for higher levels of energy efficiency? This hypothesis is tested by designing and adding a five-year consumption cost label to the tumble dryer line-up in four outlets of an Irish electrical retailer. Results show a reduction in mean energy consumption of dryers sold in treatment stores (3%, relative to control stores). However, the econometric analysis, while showing higher demand for more efficient dryers, is not statistically significant. Therefore, while it is likely that specific energy cost information is missing from the purchase decision, this omission does not appear to lead to lower levels of energy efficiency. This result is broadly in line with previous research.

1.4.4 Paper 3 – research question and preview

Informational asymmetries in relation to the energy attributes of buildings are an often cited explanation to sub-optimal efficiency standards in rental markets. Paper 3 (Chapter 4) explores the effects of independent energy ratings which are designed to remove this asymmetry, such as the BER. This rating policy, although a seemingly straightforward solution to the problem, rests upon a number of assumptions: first, that renters are attentive to energy efficiency and are willing to pay higher rents for higher efficiency standards (research question 1) and, second, that the increase in rents is sufficient to cover the investment costs of efficiency upgrades for landlords (research question 2). These research questions are tested by way of a discrete choice experiment which asks renters to choose

from a hypothetical set of single-bedroom apartments which differ according to a number of attributes, including energy efficiency. The current labelling policy (the BER) is employed for the energy efficiency attribute and, similar to Paper 2, is also converted into a monetary equivalent. Results show that renters are willing to pay more for higher energy efficiency but that the marginal increase in rents is likely below the cost of capital, on average. It is therefore unlikely that removing the informational asymmetry will promote considerable energy efficiency investment in rental markets. This result does not change when energy efficiency is communicated using a monetary equivalent.

1.4.5 Concluding chapter

The final chapter presents some concluding remarks, overarching messages for policy makers and outlines some areas for potential future work. Recent Global, European and Irish CO_2 abatement trends are also presented. The chapter illustrates the importance of information provision in energy consumption decisions, but emphasises that information will likely play a minor role in future GHG reductions relative to the other policy options described above, given the severity and scale of abatement targets.

Chapter 2

Reducing Household Electricity Demand through Smart Metering: The Role of Improved Information about Energy Saving

2.1 Introduction

Smart metering facilitates real-time communication between the customer and the utility company and enhances the potential for detailed historical and comparative consumption feedback for electricity customers. Coupled with an in-house display, households can view their electricity usage in real-time, and track their energy and cost movements with each and every turn of the switch. Such information can help households to understand what activities consume the most, and then to amend their consumption patterns, behaviours and appliance composition to reduce their electricity bill and carbon footprint. In addition, smart meters facilitate the use of time-of-use tariffs which can help reduce peak demand and smooth daily consumption (termed *demand response* programs in the literature).[3] Additional demand response can be facilitated by coupling the meter with a number of household appliances (thermostats and air-conditioning units, for example) which respond to peak signals from the meter and/or to direct signals from the utility company (known as *enabling technologies*).

[3] Newsham and Bowker (2010) discuss the main pricing alternatives within demand response trials. These are *time-of-use* (different tariffs for different times of the day), *critical peak* (higher prices applied only on pre-advertised 'event days'), *real time* (tying customer prices to wholesale electricity prices) and *peak time rebates* (refunds for reaching targets during peak/critical times).

Smart metering also provides benefits to other stakeholders of the electricity system. Electricity suppliers and generators benefit from increased grid information and smoother load profiles, both of which improve the operational efficiency and stability of the system (Faruqui et al., 2010). The potential to reduce the number and duration of blackouts (through immediate outage detection) is also highlighted by Krishnamurti et al. (2012). Nationally, potential reductions in total and peak demand and decreased variability will aid in reducing greenhouse gas emissions and, depending on the regulatory framework, the level of carbon tax. For example, Hledik (2009) suggests that the roll-out of a smart grid in the U.S. (which has smart metering and time-of-use tariffs at its core) would reduce CO_2 emissions by between 5 and 16%.

Quantifying the demand reducing effects of various levels of feedback has been the focus of a large number of studies. Faruqui et al. (2010) review the results of 12 separate trials from the USA, Canada, Australia and Japan. They find that direct feedback, in the form of an electronic in-house display (IHD), reduces demand by between 3 and 13% (average 7%). The importance of usability and clarity in such electronic feedback systems has been highlighted in Stevenson and Rijal (2010). Fischer (2008) summarises the results of twenty-two studies between 1987 and 2006. She concludes that the most effective forms of feedback are provided frequently over a long period of time, give appliance-specific breakdowns of consumption and involve electronic interaction with the households. Although not all the studies in her review show reductions, the typical savings are in the region of 5 to 12%. Abrahamse et al. (2005) also emphasises the importance of feedback frequency, but also finds that households responded well to reduction incentives in the form of financial rewards. Darby (2010a), in another extensive review of feedback mechanisms, finds that enhanced billing (more frequent and more accurate consumption information) is not always associated with lower demand, and that there is little evidence that written, generalised information (energy-saving tips) has a significant effect. Similar

findings are reported by Ofgem (2011), where the combination of generalised information and historic feedback is found to be ineffective (in the absence of smart meters). Ofgem, however, do generally find that smart metering supporting by an IHD has a significant reducing effect (around 3%). However, they also find that when the meter is installed as a 'routine replacement' and its presence not communicated effectively to the household there is no significant effect.

For time-of-use pricing, trials have shown large and significant peak reductions. Faruqui and Sergici (2011) find that peak-time rebates reduce peak demand by between 18% and 21%, and that adding an 'Energy Orb', which reminds households of peak periods (changes color depending on the tariff rate applied), increased this reduction to between 23% to 27%. Ofgem (2011) also find significant time-of-use pricing effects, but are smaller in magnitude and up to 10%. Two trials summarised by Faruqui et al. (2010) find that time-of-use and critical-peak pricing (in combination with direct feedback (IHD)) reduce peak and critical demand by 5% and 30% respectively. Newsham and Bowker (2010) also find similar reductions. Finally, Faruqui and George (2005) find that time-of-use rates with a peak to off-peak ratio of two to one produce peak reductions in the region of 5%.

In Ireland, the first major smart meter trial was undertaken between 2009 and 2010 by the Commission for Energy Regulation (CER, 2011c). The trial simultaneously applied various levels of feedback (more accurate and detailed billing and/or an IHD and generalised information/advice on how to reduce) and time-of-use tariffs to a large and representative sample of Irish households. Overall, treated households reduced their total demand by 2.5% and their peak demand by 8.8%. One interesting finding was that household reductions in peak and overall demand were not significantly different across tariff treatments – households seemed to respond to the presence of a peak/off-peak price

differential, but not its magnitude. In contrast, differences were observed in the effects of varying levels of feedback, with households receiving an IHD showing the largest reductions of 3.2% and 11.3% respectively (across all tariff rates).

This paper builds upon CER (2011c) by exploring the behavioural drivers which lead to demand reductions in the context of smart metering. To date, international trials investigating the effects of smart metering, demand response and enhanced feedback have tended to find that these sorts of measures can reduce residential energy demand, shift use away from peak times and give rise to a range of accompanying benefits for households, utility companies and the environment. However, the mechanisms behind residential demand response behaviour are still not fully understood. Underlying an information-led demand reduction is the notion that increased feedback is correcting a market failure brought about by imperfect information. Prior to smart metering, households were consuming in what was unquestionably an informational void, with little understanding of what appliances and behaviours consume the most, and when. The only feedback available was through the utility bill, which aggregated consumption over lengthy periods, disconnected instantaneous usage and behaviours from cost and often provided inaccurate consumption information due to estimation (bills based on previous readings). Smart metering has the potential to reduce this market failure by taking the imperfectly informed consumer closer to a state of *complete* consumption information (in the case of real-time electronic feedback). As highlighted by Gram-Hanssen (2010), such improvements in knowledge are a key component of bringing about a behavioural change.[4] In particular, the importance of gaining a deeper understanding of the inherent *value* that consumers place on feedback has been recently highlighted in the literature. Faruqui et al. (2010) question whether consumers actually use and benefit from this quantitative and qualitative

[4] Gram-Hanssen (2010) used *Practice Theory* to explore how households reduce their standby consumption. The theory shows how technological configurations, routines, knowledge and engagement interact to bring about changes in household behaviour.

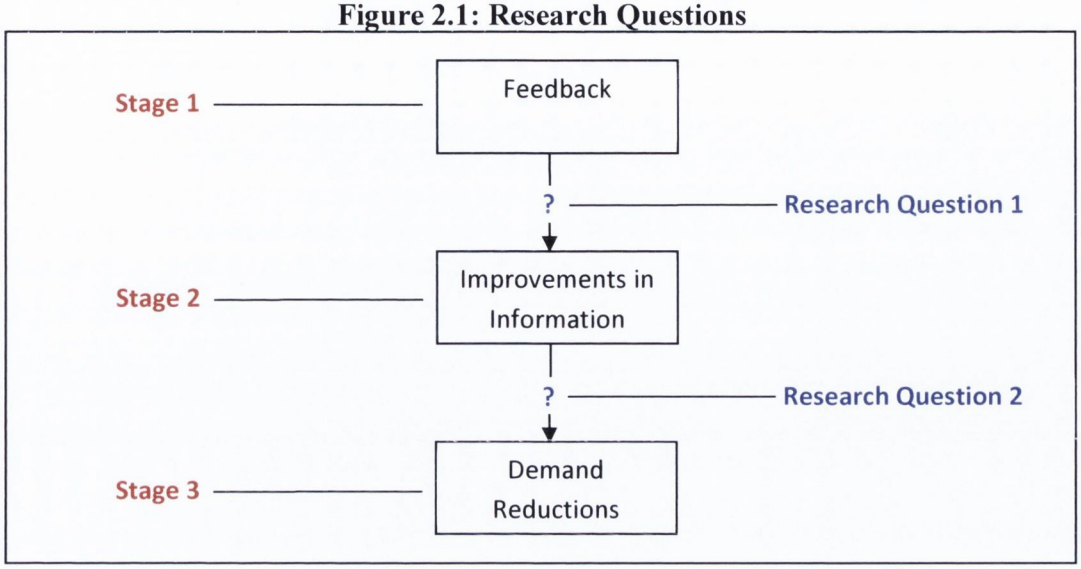
information and incorporate it into their consumption decisions, or if increased feedback simply acts as 'reminders to conserve'. This question is highly relevant for quantifying the effects of feedback in the long term – if it is the latter which is driving reductions, the effect of these reminders may diminish over longer durations and demand reductions could be short-lived.

Whether or not households actually 'learn' something new is the motivation of our first research question – *does the increased consumption feedback provided through smart meters lead to improvements in a household's stock of information about how to reduce their electricity use and which appliances consume the most*? Our second research question then seeks to quantify the effects of such, if present – *do improvements in such information help explain the demand reductions associated with the introduction of smart metering and time-of-use tariffs?* These hypotheses are summarised in Figure 2.1. A direct causal link between stage 1 and 3 is established in the literature, both in Ireland and internationally (for the most part). Significant links between stages 1, 2 and 3 would suggest that imperfect information prior to smart metering was contributing to overconsumption and that this market failure has been addressed by increased consumption feedback. If a link is observed between stage 1 and 2 but not between 2 and 3, informational improvements are not actually an important driver of demand reductions and feedback has reduced demand through some other mechanism. If this is the case, imperfect information, despite being present, was not causing overconsumption and, in short, there was no market failure to correct.

We use a household's self-reported stock of information to investigate the above. We also focus on *changes* in information rather than the *level* of information, since such indicators may be more robust to individual differences in reporting behaviour. The paper proceeds as follows: Section 2.2 outlines the data employed for this analysis and describes how

'information' change is measured in the surveys. The econometric methods are described in Sections 2.3. Section 2.4 presents the results and Section 2.5 concludes the analysis.

Figure 2.1: Research Questions



2.2 Data – The Residential Smart Meter Trial

The Irish residential smart meter trial was carried out between 2009 and 2010 and involved the installation of over 5000 smart meters into residential households (CER (2011a) and CER (2011c)).[5] The overall objective of the trial was to test the impact and viability of smart metering technology in Ireland, and to explore the demand reducing effects of various feedback mechanisms and time-of-use tariffs. Recruitment of the nationally representative stratified random sample involved a number of phased postal invitations (five), with each round adding new participants with the goal of increasing the representativeness of the sample (according to location and electricity use).

[5] The overall project commenced in 2007 and was overseen by the Commission for Energy Regulation (CER) with trials carried out by *ESB Networks* and *Electric Ireland*.

A benchmark analysis was conducted (July to December 2009) where pre-trial demand data (half-hourly readings) was collected and control/treatment groups were established.[6] During the test period (January to December 2010), treated households received one of three levels of feedback and were assigned to one of four tariff rates. The control group, which also had smart meters installed, did not receive any new information and also had no changes to their usual billing process. In addition to demand data, pre and post-trial surveys were carried out (late 2009 and early 2011 respectively), in which a large amount of household information was collected, including characteristics of the dwelling (including building type and size, appliances use and heating/water systems), demographics and attitudes towards energy use.

Feedback stimuli were applied to households in three treatment groups. All treated households received a new *Energy Usage Statement* which contained detailed information on the household's electricity use by day of the week, time-of-use and relative to previous bills and other customers, plus more generalised information detailing average appliance consumption levels and tips to lower costs, particularly during peak times.[7] One group (*BI-MST* henceforth) received just the energy statement on a bi-monthly (every two months) basis, while a second group (*MST*) was billed on a more frequent monthly basis. The third group (*IHD*) received an electronic in-house display in combination with the bi-monthly usage statement.[8] This unit provided real-time consumption, cost and tariff information.

Four time-of-use tariff types were developed (Table 2.1). While the control group were charged their usual 14.1 cent per kilowatt hour (c/kWh), the treatment tariffs (A through D)

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[6] Using available usage data and pre-trial survey responses, an allocation algorithm ensured that each cell (feedback and tariff combination) was approximately the same across a number of behavioural, demographic and attitudinal perspectives. See CER (2011b) for further details.

[7] We acknowledge that such generalized information is not 'feedback'. This information, however, is auxiliary to consumption feedback, in that it aids households to act upon their specific feedback. However, both 'feedback' and 'generalized information' would both improve what we define as 'knowledge' below.

[8] A third stimulus – an *Overall Load Reduction* (OLR) – financially rewarded households for meeting a reduction target. This stimulus is excluded from our analysis as the data was unavailable.

generally involved large price increases during peak day-time hours and reductions for night-time hours to reflect the underlying wholesale cost of electricity at these times (all prices exclude value added tax). The time-of-use price increases/decreases were designed to keep the average household's electricity cost unchanged (peak cost increases to balance with savings off-peak).[9] The samples receiving each treatment combination are displayed in Table 2.2.

Table 2.1: Time-of-use Tariffs (€/kWh) excluding VAT

	Night	Day	Peak
Tariff A	0.120	0.140	0.200
Tariff B	0.110	0.130	0.260
Tariff C	0.100	0.130	0.320
Tariff D	0.090	0.120	0.380

Table 2.2: Treatment Matrix

		Feedback Stimulus				
		CONTROL	BI-MST	MST	IHD	TOTAL
Tariff	CONTROL	758	0	0	0	**758**
	A	0	225	237	232	**694**
	B	0	90	96	82	**268**
	C	0	249	244	232	**725**
	D	0	92	95	90	**277**
	TOTAL	**758**	**656**	**672**	**636**	**2,722**

The pre and post-trial surveys explore each household's self-reported stock of information on how to reduce their electricity usage. The informational statements – to which there are five response options from strongly agree ('1') to strongly disagree ('5') – are summarised in Table 2.3 and 2.4. '*K1*' explores self-reported information on electricity reducing actions (termed 'general information' henceforth) and asks respondents if '*I know what I need to do in order to reduce electricity usage*'. This first statement is unquestionably broad, and the types of information captured by such a question could range from operational (knowing how to adjust appliance controls to save electricity) to behavioural

[9] A fifth 'weekend' tariff also involved large increases at peak times, but only on weekdays. This treatment was not combined with a feedback stimulus and is therefore not considered.

(remembering to switch off appliances when leaving the room) to technical (understanding the energy efficiency technologies available). '*K2*' explores the self-reported stock of information about appliance consumption (termed 'appliance information' henceforth) and households were asked to agree/disagree with the statement – *'I do not know enough about how much electricity different appliances use in order to reduce my usage'*. These data are used to create two response change categorical variables with three outcomes (bottom of tables): 'moved to disagree', 'no change' and 'moved to agree'. Deteriorations in self-reported information could be the result of confusion or perhaps information overload for some of the trial households.

For *K1* (Table 2.3), the majority (59% for total sample) reports that they have a good understanding of electricity reducing methods (responded with either a '1' or '2'). However, there remains a large proportion of the sample who lie somewhere between 'strongly disagree' and 'neutral'. The positive mean response change of 0.48 implies that households, on average, moved almost half a unit of response in the direction of 'strongly agrees'. Furthermore, there are a large proportion of households stating an improvement (46% compared to 22% deterioration). While this is observed in both the control and treatment groups, the increase is significantly larger in the latter (comparing differences in mean change), particularly so for the IHD category, where the percentage of 'strongly agree' responses almost doubled.[10]

For *K2* (Table 2.4), the pre-trial mean response of 2.5 (total sample) indicates that households, in general, consider their lack of information about appliances to be an impediment to their demand reductions (57% agree, 29% disagree and 14% neutral). There is, however, a large improvement (shift towards 'strongly disagree') post-trial, particularly so for the treatment group (mean change in response is -0.39 units for the control group and -0.68 average across all treatment groups). Both

[10] Significance here refers to a two-sample mean-comparison t-tests (at a 95% confidence level) comparing the mean change of control and treatment group.

are significantly different to zero and the treatment mean is significantly larger than the control. The move towards disagree is particularly large for the IHD group who, on average, show an almost full unit shift in that direction. Section 2.4.1 formalises these preliminary investigations.

Table 2.3: K1 Descriptive Statistics

K1: "I know what I need to do in order to reduce electricity usage"

	PRE-TRIAL RESPONSE				
	TOTAL	**CONTROL**	**BI-MST**	**MST**	**IHD**
1 - 'Strongly Agree' (%)	26.82%	26.78%	29.57%	25.89%	25.00%
2	31.93%	32.59%	30.18%	32.44%	32.39%
3	18.74%	17.68%	20.43%	16.96%	20.13%
4	15.03%	15.30%	14.33%	14.73%	15.72%
5 - "Strongly Disagree' (%)	7.49%	7.65%	5.49%	9.97%	6.76%
Mean Response	2.44	2.44	2.36	2.50	2.47
	POST-TRIAL RESPONSE				
	TOTAL	**CONTROL**	**BI-MST**	**MST**	**IHD**
1 - 'Strongly Agree' (%)	45.79%	37.63%	50.77%	46.47%	49.82%
2	28.11%	27.96%	26.15%	29.06%	29.32%
3	14.47%	17.57%	13.33%	14.12%	12.23%
4	7.23%	10.69%	4.96%	6.24%	6.47%
5 - "Strongly Disagree' (%)	4.40%	6.15%	4.79%	4.11%	2.16%
Mean Response	1.96	2.20	1.87	1.92	1.82
	RESPONSE CHANGE				
	TOTAL	**CONTROL**	**BI-MST**	**MST**	**IHD**
Moved to Disagree (%)	21.62%	27.23%	20.34%	20.36%	17.45%
No Move (%)	32.35%	33.24%	34.19%	30.38%	31.47%
Moved to Agree (%)	46.03%	39.53%	45.47%	49.26%	51.08%
Mean Change (Pre minus Post Response)	0.48	0.26	0.49	0.53	0.67

Table 2.4: K2 Descriptive Statistics

K2: "I do not know enough about how much electricity different appliances use in order to reduce my usage"

	PRE-TRIAL RESPONSE				
	TOTAL	**CONTROL**	**BI-MST**	**MST**	**IHD**
1 - 'Strongly Agree' (%)	32.32%	32.79%	30.87%	32.67%	32.85%
2	25.11%	25.91%	26.93%	23.51%	23.99%
3	13.80%	14.98%	12.28%	14.35%	13.37%
4	14.82%	12.15%	14.33%	16.18%	17.07%
5 - "Strongly Disagree' (%)	13.95%	14.17%	15.59%	13.28%	12.72%
Mean Response	2.53	2.49	2.57	2.54	2.53
	POST-TRIAL RESPONSE				
	TOTAL	**CONTROL**	**BI-MST**	**MST**	**IHD**
1 - 'Strongly Agree' (%)	20.19%	24.55%	20.11%	20.00%	15.10%
2	17.87%	20.36%	17.11%	18.99%	14.36%
3	15.04%	16.47%	15.52%	15.46%	12.34%
4	20.73%	17.96%	20.46%	20.50%	24.68%
5 - "Strongly Disagree' (%)	26.17%	20.66%	26.81%	25.04%	33.52%
Mean Response	3.15	2.90	3.17	3.12	3.47
	RESPONSE CHANGE				
	TOTAL	**CONTROL**	**BI-MST**	**MST**	**IHD**
Moved to Disagree (%)	49.68%	44.31%	47.80%	49.75%	58.20%
No Move (%)	25.33%	27.84%	27.16%	24.54%	21.18%
Moved to Agree (%)	24.99%	27.84%	25.04%	25.71%	20.63%
Mean Change (Pre minus Post Response)	-0.60	-0.39	-0.57	-0.58	-0.92

To investigate if self-reported changes in the stock of information differed by household type/demographic, data from the pre-trial survey is employed. Six categorical variables, including tenure, building type, age, education, gender and children, are created and Table A.1 (Appendix A) presents their descriptive statistics. Finally, the electricity demand data is collected at half-hourly intervals. This is aggregated for peak, off-peak and total consumption by household and by year (benchmark and trial) and descriptives are presented in Table A.2 (Appendix A).[11]

[11] While trial data spans all of 2010, pre-trial (benchmark) data is only available from July 14th, 2009. To avoid seasonal variations in consumption, only data from this date is used for 2010.

2.3 Methods

A multinomial logit (MNL) model is used to explore if treatment increased the self-reported stock of information about energy efficiency options (research question one). As the model is standard its description is left to Appendix A.[12] The MNL model is employed when there is no obvious order in the dependent variable. In this application, the information change variable takes on three values – improvements, no change or deteriorations. Two sets of MNL models are estimated in Section 2.4 below. In the first set (Section 2.4.1), each information change variable is regressed upon an overall treatment dummy (all feedback stimuli combined) and then upon the individual feedback stimuli simultaneously (control group the excluded reference category). The second set of models (Section 2.4.2) then re-estimate the models of Section 2.4.1 but interact a number of socio-demographic variables with the treatment dummies. MNL models are estimated for each of the six demographic variables separately and results are summarised as marginal effects in Tables 2.9 and Table 2.10 for each information change variable respectively.[13] The estimation of marginal effects for interaction variables is less straightforward in non-linear models. The approach taken follows the applied methodology presented in Karaca-Mandic et al. (2012) and we compare the change in the predicted probability for a one unit change (zero to one) in the categorical demographic variable being analysed (further details/examples provided below in Section 2.4.2).

A difference-in-difference (DID) approach is employed to investigate the effects that improvements/deteriorations in the self-reported stock of information may have had on electricity demand (research question two). The DID model can be employed to explore the effects of a policy change when data from two periods (pre and post-policy) and two

[12] The model is estimated using STATA version 11.2.

[13] Estimating these interactions simultaneously is not possible due to the size of the dataset. The results are summarized as it would not be possible to present full results from the 24 models (six separate demographic interactions by overall treatment and by stimulus for both knowledge statements).

groups (treated and untreated) are available. The DID model is generally estimated by pooled Ordinary Least Squares and is described by (see Wooldridge (2010), for example):

$$y_{it} = \beta_0 + \beta_1 Y2_{it} + \beta_2 T_i + \beta_3 Y2_{it} T_i + u_{it} \quad (1)$$

where y_{it} is electricity demand for household i in period t, $Y2$ is the period two dummy and T is the treatment dummy (u_{it} the usual noise term). The coefficient β_1 describes the temporal change in demand for the control group and β_2 describes the difference in demand between control and treatment groups in period one. The main coefficient of interest is the interaction term β_3, which describes how the demand of the treatment group changed in period two (compared to the control group), or more formally:

$$\beta_3 = (\bar{y}_{T,Y2} - \bar{y}_{T,Y1}) - (\bar{y}_{C,Y2} - \bar{y}_{C,Y1}) \quad (2)$$

where subscript C represents the control group. The model can also be estimated in a panel data setting by adding a fixed effect (e_i) to the error term and using a Within Regression Estimator. However, all time-invariant terms, such as T_i, are swept away by this time-invariant unobserved heterogeneity term and the model then reduces to:

$$y_{it} = \beta_0 + \beta_1 Y2_{it} + \beta_3 Y2_{it} T_i + e_i + u_{it} \quad (3)$$

In Section 2.4.3, this model is employed to explore the effects of treatment on electricity demand (for comparison against the original CER reports). Section 2.4.4 then explores if improvements in the self-reported stock of information help explain these reductions by adding further interactions (the information change variables) with each treatment group.

2.4 Results

2.4.1 The effects of treatment on the households' stocks of information

The MNL results and marginal effects of treatment on *K1* change (general energy reducing information) are displayed by overall treatment ('TREAT' – all feedback stimuli combined) and by individual feedback in Tables 2.5 and 2.6 respectively. Section 2.2 showed that, prior to the trial, almost 60% of the sample felt they had a sufficient understanding of electricity reducing actions (either agreed or strongly agreed with the statement). Results show that trial participation has increased this proxy for the stock of information further, with improvements significantly larger in the treatment groups. Overall (Table 2.5), the marginal effects demonstrate that treatment significantly increases the probability of improving the stock of information ('moved to agree') by 8.9 percentage points and reduces the probability of lowering the stock of information (move to disagree) by 7.3 percentage points compared to the control group. This effect is highest for the MST and the IHD (Table 2.6), where households are 9.7 and 11.5 percentage points more likely than the control group to show improvements.

Table 2.5: Mlogit Results – Effect of Treatment (overall) on K1

K1 "I know what I need to do in order to reduce electricity usage"

	Coef.	Std. Err.	DY/DX	Std. Err.
Outcome 1 – Moved to Disagree:				
TREAT (D)	-0.291**	0.120	-0.073***	-0.017
Constant	-0.207**	0.098	-	-
Outcome 2 – No Change (base):				
TREAT (D)	-	-	-0.016	-0.021
Constant	-	-	-	-
Outcome 3 – Moved to Agree:				
TREAT (D)	0.245**	0.105	0.089***	-0.022
Constant	0.167**	0.090	-	-

Model Stats:			
N	2445	LR chi test stat.	22.07
Log-Likelihood	-2565.403	P > chi	0.000
Pseudo R-Squared	0.0043		

Note: 'TREAT' is a dummy variable capturing overall treatment. 'DY/DX' indicates marginal effect and significance levels are highlighted by '' (1%), '**' (5%) and '*' (10%).***

Table 2.6: Mlogit Results – Effect of Feedback Stimuli on K1

K1 "I know what I need to do in order to reduce electricity usage"

	Coef.	Std. Err.	DY/DX	Std. Err.
Outcome 1 – Moved to Disagree:				
BI-MST (D)	-0.309*	0.024	-0.070***	0.024
MST (D)	-0.19	0.023	-0.067***	0.024
IHD (D)	-0.389**	0.000	-0.097***	0.023
Constant	-0.207**	0.000	-	-
Outcome 2 – No Change (base):				
BI-MST (D)	-	-	0.009	0.027
MST (D)	-	-	-0.03	0.026
IHD (D)	-	-	-0.018	0.027
Constant	-	-	-	-
Outcome 3 – Moved to Agree:				
BI-MST (D)	0.112	0.000	0.058**	0.028
MST (D)	0.314**	0.028	0.097***	0.027
IHD (D)	0.311**	0.027	0.115***	0.028
Constant	0.168*	0.000	-	-

Model Stats:			
N	2445	LR chi test stat.	27.330
Log-Likelihood	-2562.77	P > chi	0.000
Pseudo R-Squared	0.0053		

Note*: *'BI-MST' refers to the bi-monthly statement, 'MS' to monthly statement and 'IHD' to the in-house display.

A household's self-reported stock of information on appliance consumption is explored in *K2*. Overall (Table 2.7), treated households are significantly more likely to show an improvement (move to disagree for *K2*) than the control group. Specifically, the marginal effects demonstrate that trial participation increases the probability of an improvement by 7.5 percentage points and lowers the probability of a deterioration by 3.9 percentage points. Table 2.8 again shows the IHD to be the most important stimulus for improving the stock of information (BI-MST not significant here) and households who received the treatment are 13.9 percentage points more likely to show an improvement than the control group.

Table 2.7: Mlogit Results – Effect of Treatment (overall) on K2

K2 "I do not know enough about how much electricity different appliances use in order to reduce my usage"

	Coef.	Std. Err.	DY/DX	Std. Err.
Outcome 1 – Moved to Disagree:				
TREAT (D)	0.293***	0.110	0.075***	0.023
Constant	0.461***	0.093	-	-
Outcome 2 – No Change (base):				
TREAT (D)	-	-	-0.036*	0.019
Constant	-	-	-	-
Outcome 3 – Moved to Agree:				
TREAT (D)	-0.014	0.124	-0.039**	0.019
Constant	-0.011	0.103	-	-

Model Stats:			
N	2382	LR chi test stat.	10.79
Log-Likelihood	-2475.96	P > chi	0.0045
Pseudo R-Squared	0.002		

Table 2.8: Mlogit Results – Effect of Feedback Stimuli on K2

K2 "I do not know enough about how much electricity different appliances use in order to reduce my usage"

	Coef.	Std. Err.	DY/DX	Std. Err.
Outcome 1 – Moved to Disagree:				
BI-MST (D)	0.108	0.028	0.035	0.028
MST (D)	0.236*	0.028	0.053*	0.028
IHD (D)	0.553***	0.028	0.139***	0.028
Constant	0.461***	0	-	-
Outcome 2 – No Change (base):				
BI-MST (D)	-	-	-0.009	0.025
MST (D)	-	-	-0.032	0.025
IHD (D)	-	-	-0.068***	0.025
Constant	-	-	-	-
Outcome 3 – Moved to Agree:				
BI-MST (D)	0.000	0.000	-0.027	0.025
MST (D)	-0.027	0.025	-0.021	0.025
IHD (D)	-0.021	0.025	-0.071***	0.024
Constant	-0.071	0.024	-	-

Model Stats:			
N	2382	LR chi test stat.	25.03
Log-Likelihood	-2468.85	P > chi	0.000
Pseudo R-Squared	0.005		

In summary, there is strong evidence that time-of-use tariffs and increased levels of feedback increase a household's self-reported stocks of both general and appliance-related information on efficiency options. In both cases, receiving the IHD has the strongest effect, followed by the MST and BI-MST respectively (the latter not significant for *K2*). This is consistent with the amount of 'feedback' that each stimulus contains.

2.4.2 Socio-demographic interactions

Table 2.9 and 2.10 present the marginal effects of feedback for a number of socio-demographic indicators.[14] The last column of these tables describes the overall treatment effect for each demographic, while columns one through three show the effect by feedback stimulus. Each marginal effect gives the percentage point change in probability for a zero-one change in the categorical demographic relative to the reference group (the excluded category within the demographic variable being explored). To illustrate, in Table 2.9, the marginal effect of TENURE1 at BI-MST on 'moved to disagree' is -0.13 which implies that renters who received this stimulus are less likely to show a deterioration (decreases the probability by 13 percentage points) than non-renters (households who own outright or have a mortgage). This is, however, the only significant effect for tenure and, in general, renters did not respond any different to treatment. The house-type interactions show similar results with apartment dwellers responding no differently to overall treatment or to each individual stimulus (than non-apartment dwellers). The age categories are significant at BI-MST (also overall for the oldest age category) where the results demonstrate that younger households (18-35 years; the base category) are 17 percentage points more likely than AGE2 (36-55 years) and 12 percentage points more likely than AGE3 (55+ years) to improve their self-reported stock of general information on how to reduce consumption.[15] The presence of children is significant (overall) – households without children are 5.3 percentage points more likely to show a deterioration. Finally, the interaction of gender and education demonstrates that being female increases the probability of a 'no change' while households with a third level education are significantly more likely to show an improvement (4.4 percentage point increase, overall).

[14] Tables 2.9 and 2.10 display the marginal effect and the statistical significance indicator only. These tables summarise the results from twelve separate regressions and it is therefore not possible to display the full results.

[15] The effects of the two age categories are estimated simultaneously. The reference group is therefore AGE1 (young households).

The interacted marginal effects for *K2* (appliance information) are displayed in Table 2.10 and show a small number of significant effects. Renting households display a negative treatment effect at 'moved to disagree' (overall). This therefore implies that non-renters are more likely to show an improvement in the stock of appliance information than renters (probability of a move to disagree 9.3 percentage points higher). In this regard, the MST appears to be particularly valuable to non-renters, who are over 15.2 percentage points more likely to show an improvement. While age and the presence of children show no significant effects, households headed by females are more likely (4.2 percentage points) to show an improvement, overall. For education, it is possible that third-level households benefited from the IHD, but only in that they are significantly less likely to show a deterioration (reduces the probability of a deterioration by 6 percentage points).

Table 2.9: Summary of Socio-Demographic Marginal Effects for K1

K1 "I know what I need to do in order to reduce electricity usage"

	BI-MST	MST	IHD	TREAT
TENURE1 (households that rent)				
Moved to Agree	0.028	0.009	-0.136	-0.034
Moved to Disagree	-0.130**	-0.010	0.002	-0.039
No Change	0.102	0.002	0.133	0.073
HOUSE1 (apartments)				
Moved to Agree	0.120	0.081	0.036	0.076
Moved to Disagree	-0.062	-0.062	-0.085	-0.076
No Change	-0.057	-0.018	0.049	-0.001
AGE2 (36-55 years)				
Moved to Agree	-0.170***	0.011	-0.056	-0.076
Moved to Disagree	-0.020	-0.042	-0.038	-0.029
No Change	0.190***	0.031	0.093	0.105
AGE3 (55+ years)				
Moved to Agree	-0.120*	-0.035	-0.092	-0.087**
Moved to Disagree	-0.034	-0.033	0.038	-0.007
No Change	0.154**	0.068	0.054	0.094**
CHILD (presence of children under 15 years)				
Moved to Agree	0.073	0.036	0.014	0.041
Moved to Disagree	-0.077**	-0.014	-0.074**	-0.053***
No Change	0.005	-0.022	0.060	0.013
FEMALE (female respondent)				
Moved to Agree	-0.065	-0.069*	0.009	-0.044*
Moved to Disagree	0.038	0.000	-0.051	-0.003
No Change	0.026	0.069*	0.042	0.047**
EDU3 (third level education)				
Moved to Agree	0.066	-0.005	0.071	0.044*
Moved to Disagree	-0.020	-0.003	-0.036	-0.020
No Change	-0.046	0.007	-0.034	-0.024

Table 2.10: Summary of Socio-Demographic Marginal Effects for K2

K2 "I do not know enough about how much electricity different appliances use in order to reduce my usage"

	BI-MST	MST	IHD	TREAT
TENURE1 (households that rent)				
Moved to Agree	0.073	0.072	-0.031	0.033
Moved to Disagree	-0.124	-0.152*	-0.025	-0.093*
No Change	0.051	0.081	0.057	0.061
HOUSE1 (apartments)				
Moved to Agree	-0.253***	0.078	-0.025	-0.079
Moved to Disagree	0.021	0.172	0.055	0.083
No Change	0.232	-0.249***	-0.030	-0.004
AGE2 (36-55 years)				
Moved to Agree	0.039	-0.055	-0.060	-0.023
Moved to Disagree	-0.032	0.027	0.041	0.007
No Change	-0.006	0.029	0.020	0.017
AGE3 (55+ years)				
Moved to Agree	0.089	-0.047	-0.008	0.013
Moved to Disagree	-0.074	0.076	-0.031	-0.012
No Change	-0.015	-0.029	0.039	-0.001
CHILD (presence of children under 15 years)				
Moved to Agree	-0.046	-0.053	-0.006	-0.035
Moved to Disagree	0.068	-0.012	0.020	0.024
No Change	-0.023	0.065	-0.014	0.011
FEMALE (female respondent)				
Moved to Agree	-0.012	0.037	0.012	0.013
Moved to Disagree	0.062	0.016	0.053	0.042*
No Change	-0.049	-0.054	-0.065*	-0.055***
EDU3 (third level education)				
Moved to Agree	0.006	0.033	-0.060*	-0.007
Moved to Disagree	0.030	-0.045	0.015	0.001
No Change	-0.035	0.011	0.046	0.006

2.4.3 The effects of treatment on demand

Table 2.11 displays the effect of each stimulus on total, peak and off-peak demand using the DID model. Table 2.12 summarises these effects as percentage changes. The coefficient for Y2 (2010 dummy variable) describes the change in demand for the control group between the benchmark period (2009) and the treatment period (2010), and is not significant, as expected. The main variables of interest are the interaction terms which describe the difference in 2010 demand for each feedback stimuli (compared to the control group), and it is evident that treatment has significantly reduced total demand in 2010.[16] For example, the MST has the largest effect and has lowered total demand by 60.33 kWh or by 2.9% (versus control group levels in the treatment year). This is followed by the IHD and BI-MST (the latter not significant), which show reductions of 43.03 kWh (2.1%) and 7.13 kWh (0.4%) respectively. Overall (all feedback groups combined), treatment has significantly lowered total demand by 36.95 kWh (1.8%).[17] Subsequent auxiliary regressions (not displayed) also show that these feedback-led reductions differ by a household's appliance composition (interacting feedback stimuli with appliance dummies). For example, households with high-consuming devices, such as electric immersion heaters (77% of the sample) and storage heaters (4%), show larger reductions than households without.[18] However, this is perhaps expected as households without such items have significantly lower electricity demand and thus less capacity to reduce.

Peak reductions are relatively higher, and treatment is significant both overall and by feedback type. The average peak reduction is 7.8%, and this is strongest for the IHD (9.4%), followed by the MST (8.7%) and the BI-MST (5.4%). Furthermore, the majority of

[16] We have not included additional tariff interactions as the subgroups would no longer be representative. The trial was designed to be representative at the stimuli level and also at the tariff level only.
[17] Model results for the overall effect are not shown, but are estimated using the same methodology but replacing the individual feedback dummy variables with the single overall treatment dummy (TREAT).
[18] These secondary results, while certainly of a general interest, extend beyond our core research questions. To maintain clarity, therefore, we have not included these extra tables of results.

the total demand reductions occurred during peak times – overall, 59% of total reductions occurring during this two hour period. This dominant peak effect is also supported by the lack of significance at off-peak times, both overall and by stimulus, in all but the MST.

Table 2.11: DID FE Model Results - Effect of Feedback Stimuli on Demand

	TOTAL		PEAK		OFF-PAEK	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Y2 (D)	6.168	14.622	-1.957	2.360	8.125	12.998
Y2 * BI-MST	-7.127	21.467	-15.099***	3.465	7.972	19.083
Y2 * MST	-60.333***	21.330	-24.585***	3.443	-35.748*	18.961
Y2 * IHD	-43.033**	21.648	-26.583***	3.494	-16.450	19.244
Constant	2091.660	5.456	290.235	0.881	1801.425	4.850
Model Stats:						
Observations	5444		5444		5444	
Groups	2722		2722		2722	
F stat.	4.42		70.18		1.52	
Prob. > F	0.000		0.000		0.195	

Note: 'DID' indicates difference-in-difference model and 'FE' indicates fixed effects. 'Y2' is the treatment period dummy.

Table 2.12: Percentage Reductions in Treatment Groups

	TOTAL	PEAK	OFF-PEAK
BI-MST	-0.348	-5.371***	0.452
MST	-2.949***	-8.746***	-2.025*
IHD	-2.103**	-9.456***	-0.932
TREAT	-1.806**	-7.849***	-0.844

Note: Reductions are relative to the control group demand levels in the treatment year

2.4.4 The effects of changes in the self-reported stock of information on demand

The previous section has shown a significant reduction in total and peak demand as a direct result of treatment. Using the same DID methodology, this section explores if this decrease can be explained by an improvement in a household's self-reported stock of information (Research Question Two). The results in Table 2.13 show the effects of a change in *K1*

(general information) on total, peak and off-peak demand. Between pre and post-surveys, 48% of households (treated) showed an improvement in their general information, 20% showed a deterioration and 32% did not change their response. This information-change categorical variable has been disaggregated into five groups to investigate the consistency of the correlations – a large improvement, for example, should, if relevant, lead to a larger decrease in demand than a small improvement.[19]

The 2010 dummy, in this setting, describes the change in demand for control households that showed no improvement or deterioration in their self-reported general information (the excluded reference group for the informational change dummy variables). These households increased their total demand by 49.47 kWh (compared to 2009). The stimuli interactions show how this differed for treated households (again, for those who kept their response unchanged).[20] The three-way interactions then show if treated households reporting informational improvements/deteriorations reduced significantly more/less. In this regard, there are few significant effects, and where significant, the coefficients are not of the expected sign. For example, for the MST and IHD, households with large improvements ('large move to agree') have significantly higher total demand in 2010 than households who kept their response unchanged (higher even than households who showed a deterioration). Furthermore, for peak and off-peak, improvements, large or small, do not accompany significantly larger reductions and, again, in most cases, the signs even suggest the opposite. Table 2.14 shows the effect of appliance information change (*K2*) on demand. As with *K1*, there are few significant three-way interaction effects and the direction of the relationship is inconsistent with expectations. In only a number of cases – for example,

[19] For the knowledge change variables a 'large move' indicates a 3 or 4 unit shift in response and a 'small move' indicates a 1 or 2 unit shift. For example, if a household responded with a 1 in the pre-trial survey and a 4 in the post-trial survey, their change of -3 would be represented as a 'large move to disagree'.

[20] Although these appear considerably larger than Section 2.4.3, the net effect [Y2 + (Y2 * TREATMENT)] is closer to Table 2.13.

households with the MST and small improvements ('small move to disagree') – is the sign of the coefficient as expected (but, again, is not significant).

These results appear to be robust to a household's endowment of appliances (not shown). For example, interacting the self-reported information variables with appliance dummies (estimated separately for immersion and storage heaters) does not change this general result.[21] Furthermore, if we exclude households who started with a high initial stock of information from the analysis (households that could not improve) our conclusions, in general, do not change.[22]

[21] We test this as households without these high-consumption items may 'feel' their knowledge has increased but, without these items, may have no capacity to make sizable reductions. Given the small sample size, we avoided a fourth interaction and tested this hypothesis on treated households only (exclude the control group).

[22] With one exception for appliance knowledge (out of twelve knowledge-feedback interactions) – households with the MST who made a 'small move to disagree' (a small improvement) had significantly lower off-peak demand in the reduced sample. This is, however, clearly an isolated result among many tests.

Table 2.13: DID FE model results – Effect of K1 Change on Total Demand

K1 "I we know what I we need to do in order to reduce electricity usage"

	TOTAL		PEAK		OFF-PAEK	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Y2	49.473*	26.566	2.811	4.320	46.662**	23.616
Y2 * BI-MST	-74.976*	38.817	-20.174***	6.312	-54.802	34.507
Y2 * MST	-125.273***	39.645	-30.076***	6.446	-95.197***	35.243
Y2 * IHD	-105.564***	40.264	-34.774***	6.547	-70.789**	35.794
Y2 * Large move to disagree	-21.214	81.482	-0.663	13.249	-20.551	72.435
Y2 * Small move to disagree	-62.794	41.393	-10.393	6.731	-52.401	36.797
Y2 * Small move to agree	-32.140	38.183	-1.369	6.209	-30.771	33.943
Y2 * Large move to agree	-179.421***	59.299	-19.203**	9.642	-160.218***	52.715
Y2 * BI-MST * Large move to disagree	130.917	122.757	12.873	19.961	118.044	109.127
Y2 * BI-MST * Small move to disagree	170.999***	64.414	21.474**	10.474	149.525***	57.262
Y2 * BI-MST * Small move to agree	74.151	55.072	3.162	8.955	70.990	48.957
Y2 * BI-MST * Large move to agree	62.818	83.862	-1.484	13.636	64.302	74.550
Y2 * MST * Large move to disagree	91.664	132.357	20.420	21.521	71.244	117.660
Y2 * MST * Small move to disagree	72.227	63.740	4.066	10.364	68.161	56.662
Y2 * MST * Small move to agree	65.320	54.850	-0.187	8.919	65.508	48.760
Y2 * MST * Large move to agree	280.115***	82.521	33.446**	13.418	246.668***	73.359
Y2 * IHD * Large move to disagree	20.699	126.439	0.155	20.559	20.545	112.400
Y2 * IHD * Small move to disagree	23.244	68.431	3.209	11.127	20.035	60.832
Y2 * IHD * Small move to agree	69.784	56.168	8.835	9.133	60.950	49.932
Y2 * IHD * Large move to agree	213.775***	80.373	18.809	13.069	194.966***	71.449
Constant	2100.260***	5.738	292.418***	0.933	1807.841***	5.101
Model Stats:						
Observations	4866		4866		4866	
Groups	2433		2433		2433	
F stat.	2.27		12.37		1.65	
Prob. > F	0.0011		0		0.0341	

Table 2.14: DID FE model results – Effect of K2 Change on Total Demand

K2: "I do not know enough about how much electricity different appliances use in order to reduce my usage"

	TOTAL		PEAK		OFF-PEAK	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Y2	19.271	29.377	0.593	4.779	18.678	26.123
Y2 * BI-MST	-31.263	43.650	-15.675**	7.101	-15.588	38.815
Y2 * MST	-68.975	44.300	-29.203***	7.206	-39.771	39.393
Y2 * IHD	-100.047**	47.527	-40.724***	7.731	-59.323	42.263
Y2 * Large move to disagree	-86.973*	50.524	-14.443*	8.219	-72.530	44.928
Y2 * Small move to disagree	2.319	40.763	-2.110	6.631	4.428	36.248
Y2 * Small move to agree	3.927	45.013	2.161	7.322	1.766	40.027
Y2 * Large move to agree	24.666	64.863	2.772	10.551	21.894	57.678
Y2 * BI-MST * Large move to disagree	69.678	72.339	8.313	11.768	61.365	64.327
Y2 * BI-MST * Small move to disagree	52.344	60.264	6.453	9.803	45.891	53.589
Y2 * BI-MST * Small move to agree	-2.157	66.907	-8.645	10.884	6.487	59.496
Y2 * BI-MST * Large move to agree	-2.603	104.797	-0.070	17.048	-2.533	93.189
Y2 * MST* Large move to disagree	122.205*	71.588	14.371	11.645	107.834*	63.658
Y2 * MST* Small move to disagree	-78.708	60.162	-9.325	9.787	-69.383	53.498
Y2 * MST* Small move to agree	38.044	67.333	11.908	10.953	26.136	59.875
Y2 * MST* Large move to agree	92.427	97.070	26.504*	15.791	65.922	86.317
Y2 * IHD* Large move to disagree	130.808*	72.129	26.891**	11.733	103.917	64.139
Y2 * IHD * Small move to disagree	47.196	62.540	12.426	10.174	34.770	55.613
Y2 * IHD* Small move to agree	31.512	73.510	8.634	11.958	22.878	65.368
Y2 * IHD* Large move to agree	26.775	103.832	21.512	16.891	5.263	92.331
Constant	2103.512***	5.816	293.051***	0.946	1810.460***	5.171
Model Stats:						
Observations	4746		4746		4746	
Groups	2373		2373		2373	
F stat.	1.88		14.57		1.18	
Prob. > F	0.0102		0		0.2626	

2.5 Discussion

This paper attempts to gain a deeper understanding of demand reductions by exploring the role of increasing a household's stock of information about energy use and efficiency options through improved feedback on electricity use and exposure to time-of-use tariffs. Understanding the mechanisms of behavioural change is important for formulating policy, in particular policy that has an informational component. Three main findings are apparent. First, consistent with the original (CER, 2011c) findings, treatment has lowered demand, and in 2010, total demand is 1.8% lower than the control group. Regarding the effects of different types of feedback, households who received the monthly user statement made the largest reductions (2.9%) followed by the in-house display (2.1%) and the bi-monthly user statement (0.3% – not significant). These reductions, while generally significant, are certainly at the lower end of trial findings internationally (particularly studies that combine time-of-use and feedback), where total demand reductions are estimated to range anywhere between zero and 14%. Secondly, treatment has led to significant improvements in stocks of information reported by households on both general and appliance-related options for conserving electricity– while the control group also showed improvements, the gains for the treatment sample (overall) are significantly higher, particularly for households receiving the in-house display, which increased the probability of information gains by 11.5 and 13.9 percentage points (general and appliance respectively) relative to the control group.

Our last set of models shows no statistically significant relationship between changes in the self-reported stock of information on conservation options and in demand for electricity – in general, the results were neither significant nor consistent with expectations. During the trial a large proportion of the sample increased their self-assessed stock of information about how to reduce electricity consumption. Overall, 48% of treated households showed

improved levels of general information (35% small improvement and 11% large improvement) and 51% reported improved appliance-related information (32% small and 18% large). However, our results imply that these improvements had no significant association with the observed demand reductions and imply, for example, that the 19% of households who reported a large improvement in their appliance-related information did not reduce their electricity consumption more than households who kept their response unchanged (25% of the sample). In most cases, the signs even suggest the opposite.

Policymakers need be aware of the mechanisms by which feedback and information reduce energy demand. Feedback on energy use may make energy use more visible and provide a better understanding of what appliances and behaviours consume the most, and when. Thus it may serve to address an existing market failure brought about by imperfect information. However, our results suggest that reductions in demand following introduction of smart metering and time-of-use tariffs were not brought about by an improvement in the stock of such information, or at least the component of information correlated with the self-reported proxies available to us. In summary, we found no evidence that these informational improvements *per se* were necessary or sufficient for reducing electricity demand.

However, and crucial for policy formulation, is that these results do not indicate that feedback and time-of-use tariffs are ineffective at reducing or shifting demand, but only that they reduce demand through some other mechanism. The results suggest that frameworks which go beyond addressing imperfect information are justified. Allcott (2011), for example, suggests that many energy reducing actions, such as turning off lights, adjusting thermostats and closing blinds, are likely to be behaviours that most households are aware of already, and that feedback/information drives reductions by drawing attention

to or increasing the 'moral cost' of energy use (pg. 1088).[23] It is also possible that increased feedback simply increases the frequency of reminders, which then increases a household's motivation to reach its conservation targets (see MIT (2011) pg. 162 and Faruqui et al. (2010) pg. 1607). The real-time feedback provided by IHDs may also increase a household's sense of control and increase the rewards associated with conservation efforts. This motivational component of behavioural change has also been discussed by Gram-Hanssen (2010). The insignificant demand-reducing effects of the bi-monthly user statement versus the significant effects of the monthly (same information but more frequent) supports this possibility. Furthermore, in the demand response literature, Faruqui and Sergici (2011) show how a pure reminder (*The Energy Orb*) facilitates significantly larger peak reductions.

It is important to highlight that our results only relate to a short-run experiment – during our twelve months of data, the technologies and efficiency levels within the majority of household are fixed, particularly so for very high consumption items such as cookers, immersions and heating systems which get replaced over much longer timeframes. Over such durations, increased awareness of appliance consumption would likely motivate more efficient appliance purchases and renovation decisions, and the effects of such may outweigh any of the short-run motivation-led reductions (assuming this is the driver in the short-run). If this is the case, the appropriate policy is then to provide frequent reminders to increase a household's motivation in the short-run, but to maintain an educational component to facilitate knowledge-led reductions in the long-run. The likelihood of the latter, however, remains the work of future research using data from longer panels.

Finally, the extensive research of Ofgem (2011) also highlights a potential issue in smart metering trials which may bias the true effects of feedback. Their findings suggest that the

[23] Behavioural changes observed following the comparative feedback and generalized information provided though OPOWERS's *Home Energy Reports* in the US

physical presence of the meter is important, and that feedback – including an in-house display, energy efficiency information, historic feedback and financial incentives – in the absence of a smart meter has no effect. Of particular interest, is that when the meter is installed as a 'routine replacement' and its presence not communicated effectively to the household (in trials testing in-house displays) there is also no significant effect. It is possible that in the contemporary world of desirable 'smart' consumer products, the actual labelling of the meter may have increased a household's engagement, motivation and subsequent utilisation of informational aids. The overall potential for smart metering will therefore rest heavily on how customers are engaged and encouraged to incorporate this technology into their day-to-day behaviours (Darby, 2010b).

2.6 Conclusion

Smart metering trials in Ireland and internationally have identified significant societal benefits. International findings, while varying in magnitude, generally show that a combination of time-of-use tariffs and increased customer feedback can yield reductions in demand, particularly at peak times, and a large-scale roll-out of smart meters would lead to lower and smoother load profiles and significant reductions in CO_2. For Ireland, (CER, 2011b) explores the costs and benefits (for networks, suppliers, generators and end-users) of alternative smart metering technologies and levels of feedback, and conclude that the national rollout of smart meters would bring statistically significant and economically substantial net benefits.[24]

[24] The authors calculate the net present value of a roll-out, and state that their estimates are likely to be conservative and be at the lower end of expected benefits. They find that bi-monthly billing without the IHD generally provides the highest net present value (but including the IHD only reduces the NPV marginally in most cases). Results are, however, quite sensitive to the tariff rates chosen.

This paper has attempted to uncover the underlying drivers of such information-led reductions. Consistent with (CER, 2011c), our results show that smart metering supported by increased customer feedback helped residential customers to reduce their electricity demand. We also find that treated households increased their self-reported stock of energy-reducing information. We do not, however, find a correlation between self-reported information improvements and demand reductions. This final result does not support the hypothesis that imperfect information pre-metering (related to energy reducing actions and appliance consumption, as defined) was leading to over-consumption. It is possible then that smart-metering is effective because it acts as a reminder and motivator, rather than an educational aid.

There are, however, a number of limitations to our data. As the trial simultaneously applied time-of-use tariffs and various levels of feedback in combination, it is not possible to isolate the presence of a pure feedback-led 'conservation' effect. Although relative peak reductions are higher and suggest that the tariffs are the main behavioural driver, peak to off-peak load-shifting would have lowered a 'pure' conservation effect during off-peak times. A further limitation of the data is the reliability of our proxies for the stock of information, which are self-reported and therefore subject to measurement error. The possibility of this bias could be removed if future trials included tests of the actual information possessed by participants. Furthermore, the size of our dataset limits deeper levels of knowledge interactions which could provide further insight. For example, although large improvements in information stocks were not significant, it would be interesting to explore if households with low initial stocks of information and subsequent large improvements also showed no reduction in demand.

Chapter 3

The Energy Efficiency Gap and the Role of Estimated Lifetime Energy Cost Information

3.1 Introduction

3.1.1 Background – is there an energy efficiency gap?

There will always be an efficiency difference between our current stock of appliances and what is potentially achievable given contemporary technologies, particularly given that the pace of technical change is high and the life of appliances is long. However, from a private perspective, what matters are the welfare effects of each investment over the life of the appliance, and in this regard, buyers may not be minimising the net present value of total costs at the point of sale. Whether the focus is on appliances, modes of transportation or attributes of homes and buildings, deviations from cost-minimisation, on aggregate, have resulted in an 'energy efficiency gap' (Jaffe and Stavins, 1994a) between our present stock of appliances (the current equilibrium) and what would have been in the absence of misoptimisation (the hypothetical). Historically, this gap will have resulted in higher energy consumption, electricity generation and environmental impact.

The degree of misoptimisation, however, depends upon the breadth of costs and energy savings assumed. A starting point is to calculate a technology's upfront costs plus discounted future energy costs (using a manufacturer's ratings and mean consumption

levels).[25] For model m, the total cost of appliance ownership for individual i (with discount rate r) over appliance lifetime T is then:

$$C_{m,i} = I_m + \sum_{t=1}^{T} \frac{1}{(1+r_i)^t} * [X_{m,i,t}] \quad (1a)$$

$$X_{m,i,t} = W_{m,i}(e_m, h_i) * P(1+\pi)^t \quad (1b)$$

where I is the upfront cost of the appliance and X are the annual energy costs. Energy costs are the product of the number of energy units consumed W (a function of model efficiency, e, and the quantity of energy services demanded, h) and the price of energy, P (with inflation rate π). A researcher using such an approach would assume a reasonable discount and inflation rate, and then calculate energy costs using manufacturer's technical specifications and the average number of energy units consumed by households. 'Misoptimisation' then occurs when buyers fail to choose models with the lowest total cost (assuming all other product attributes equal and buyers are not financially constrained). In practice, however, previous research has estimated the implicit discount rates (the estimated discount rate that harmonizes the initial investment with future consumption savings) based on historical purchase decisions. In this regard, Ansar and Sparks (2009) show a median rate of 0.67 in previous studies.

The literature outlines a number of explanations for deviations from cost minimisation. A standard market failure discussed by Jaffe and Stavins (1994b) relates to the availability of auxiliary cost information. Imperfect information, on a fundamental level, implies that buyers are simply unaware of their current efficiency level or, more importantly, the costs and benefits of contemporary technologies. Furthermore, information on energy savings is often absorbed through existing buyers – a positive adoption externality which may be

[25] This is analogous to a simple 'engineering' estimate (see discussion in Alcott and Greenstone (2012), for example)

important for new technologies to reach a tipping point. There may also be asymmetric information problems between buyers and sellers of appliances at the point of sale – a salesperson's commission may not be related to the efficiency of the appliances he/she sells and therefore he/she may not be incentivised to provide such information. Given the range of informational deficiencies, it is not surprising that much public policy to date has attempted to remove this market failure through independent appliance consumption labelling.

Further potential errors and omissions in Equation 1 are the exclusion of private transaction costs and uncertainty, and the assumption of homogenous adopters (Jaffe and Stavins, 1994b). Private transaction costs can be associated with the acquisition of information prior to potential adoption. A contemporary energy-saving technology, while providing the same energy services, may require a change in adopter routines to ensure compatibility with existing household systems and processes. For example, switching from private to public transport often requires a considerable change in household routines, and this learning process represents a real cost in terms of both time and effort for the potential adopter.

Furthermore, post-adoption, there may be costs associated with unobserved quality differences embedded in new technologies (Jaffe and Stavins, 1994a). For example, electric vehicle owners must adapt their driving behavior according to the limits of this new technology (lower range, longer refueling etc.). Such changes in behaviour, again, represent real costs to the adopter, and while difficult to quantify, will be inappropriately labelled as misoptimisation if unaccounted for in a simple NPV calculation.

For the adopter there is also a high degree of uncertainty in estimating Equation 1 (Hassett and Metcalf, 1993). For example, pre-adopters must forecast energy inflation, appliance life and, potentially, the level of depreciation (if resale is being considered). Buyers may

even be uncertain about their expected level of use and the level of energy savings promised by manufacturers. For example, while car miles-per-gallon ratings are an unbiased estimate of actual consumption, considerable variation is observed in post-sale efficiency (Greene et al., 2006) due to heterogeneous behaviours (acceleration and speed) and environment conditions (climate, traffic and road quality). Given that such uncertainty is higher for new technologies (due to lack of experience), it is then not surprising or irrational for investors to discount future energy savings heavily.

There are also a number of theories from the behavioural economics literature which can be applied to understanding the underutilisation of energy-saving technologies. Firstly, experimental studies have long supported the existence of hyperbolic discounting leading to 'present bias' or 'time-inconsistency' in decision making (Loewenstein and Prelec, 1992, Frederick et al., 2002, Laibson, 1997). This has obvious implications for energy efficiency investment, which nearly always involves trading increased immediate costs for future savings. Furthermore, and as already indicated, the decision to buy this new technology represents a choice under uncertainty. In this regard, 'Prospect Theory' (Kahneman and Tversky, 1979, Kahneman and Tversky, 1984, Tversky and Kahneman, 1986) shows that the value change associated with a loss is significantly higher than that for an equivalent gain ('loss aversion'), that choices are driven by context (framing effects) and that decision-makers overweigh certain outcomes (certainty effect). The theory helps explain why decision-makers can often favour an actuarially unfavourable alternative and are reluctant to deviate from their status quo (status quo bias) (Samuelson and Zeckhauser, 1988). For the potential adopter, this new energy-saving device could be viewed either as an uncertain gain (the energy savings) or as an uncertain loss (this newer untested technology fails) relative to the status quo (the existing inefficient technology, assumed to be a sure bet). Prospect theory tells us that buyers will undervalue uncertain gains and overvalue the uncertain losses higher than their respective risks warrant under rational

decision making, which in both cases reduce the attractiveness of an efficiency upgrade in favour of the status quo.

3.1.2 Motivation – future energy cost inattention

The energy efficiency gap as described above, regardless of the breadth of cost, discounting or behavioural assumptions included, assumes that buyers are essentially minimising some objective function that includes future auxiliary costs. Buyers may, however, be inattentive to their future energy expenditures (as discussed by Allcott and Greenstone (2012)). Alternatively, the theory of 'Bounded Rationality' (Simon, 1959) suggests that decision-makers, while fundamentally rational, can lack the cognitive abilities to process and incorporate all available information into the decision process. It is therefore possible that inattention is due to inexperience (or perhaps inability) in formulating future energy cost forecasts.

Such high calculation or transaction costs are highlighted in the surveys of Heinzle (2012), where households show substantial errors when converting energy efficiency (watts or kWh) into auxiliary cost expectations.[26] Even for vehicle auxiliary costs (a technology with considerably higher energy costs), Turrentine and Kurani (2007) show that households, in general, do not keep track of past expenditures and are therefore unlikely to have 'the basic building blocks of knowledge assumed by the model of economically rational decision-making' (pg. 1213). These results therefore suggest that households may lack a key financial input in the investment decision – the energy cost differences across new appliances and perhaps more importantly, the difference between their current stock and

[26] Heinzle (2012) shows that over 80% of respondents (German survey) miscalculated the annual cost differences of two televisions (over or under 25% of actual difference, with around two-thirds overestimating), when given each unit's consumption rating (watts), hours of use per day and the cost of electricity (€/kWh).

that of potential new purchases. Research by Sallee (2013), however, suggests that such inattention is not necessarily irrational behaviour, given the low variation in auxiliary costs within product groups and the high investment transaction costs associated with calculating and comparing models ('rational inattention').

From a policy perspective, the concern is whether or not this lack of *specific* monetary information is slowing the move to more efficient technologies, or if the non-monetary efficiency labelling currently provided is an adequate informational proxy of future costs. Current EU energy efficiency labelling provides a number of energy consumption indicators to aid comparative decision making: colour-coded efficiency bands and cycle/annual kWh estimates (an example for tumble dryers is displayed in Figure A.1 (Appendix)) and there is evidence that this information is valued by buyers and has led to increased demand for more efficient appliances (see Sammer and Wüstenhagen (2006) and Heinzle and Wüstenhagen (2012) for example).[27]

However, while quantitative indicators (kWh per cycle/annum) are comparatively informative, household inability to convert these into monetary expectations (as highlighted by Heinzle (2012)), may suggest that buyers do not fully understand this unit of measurement. Furthermore, the efficiency bands, although informative, are categorical without reference to band width and therefore do not communicate the marginal benefit (CO_2, watt or consumption cost reductions) of efficiency band improvements. Our research question is – would a continuous comparative indicator that is universally understood (money) lead to an even greater shift towards efficient purchases?

Previous research on the effects of monetary energy cost information is mixed. Kallbekken et al. (2013) find that lifetime energy cost labels combined with staff training reduces the

[27] New EU labels for dryers, which replace kWh/cycle with kWh/annum (calculated using a proportion of full and half loads, plus standby consumption), have been in place since October 2013. The new label will only apply to new models (old models maintain previous labelling).

mean consumption of tumble dryers in Norway by 4.9% (however, they also find that labels without staff training have no significant effect). In the UK, DEEC (2014) show that lifetime labels reduced washer-dryer consumption by 0.7%, but find no effect for washing machines or tumble dryers. There are also a number of previous stated preference studies. For example, Heinzle (2012) finds that displaying ten-year consumption cost information significantly increases the willingness-to-pay for more efficient televisions (choice experiment). Furthermore, Newell and Siikamäki (2013) find that the willingness-to-pay for efficient water heaters is highest when annual consumption costs are combined with more general informative aids (*Energy Star* and EU Efficiency Grades). For cars, Codagnone et al. (2013) find that information on running costs and fuel savings also have a positive effect (again using stated preference techniques). In this paper the effects of a five year consumption cost label for dryers is explored. The remainer of the paper is structured as follows: Section 2 outlines the details of the retail experiment and discusses our energy cost assumptions and experimental strategy; Section 3 discusses the econometric methods employed and Section 4 presents the results; Sections 5 and 6 provide a discussion and conclusion respectively.

3.2 Labelling Trial

The retailer (*DID Electrical*) was approached in 2013 and agreed to a three month trial (August – October) in four of its twenty outlets. There was, however, a preliminary pilot analysis conducted between May and July (two stores) to ensure that the consumption labels did not have a negative impact on dryer sales.[28] Treatment stores were selected by the retailer and are all located in the Greater Dublin area. The retailer's 16 remaining

[28] Given that clothes dryers are a more substitutable appliance (clothes airers, for example) relative to other white goods, the possibility of a negative sales effect could not be rejected ex-ante.

stores, which are located throughout Ireland, are employed as our control group (Table 3.1).

Table 3.1: Treatment/Control Trial/Pre-Trial Matrix

	P0: (March-April) Pre-Trial	P1: (May-July) Pilot	P2: (Aug-Oct) Trial
Control	no change	no change	no change
Treatment Store 1	no change	Treatment	Treatment
Treatment Store 2	no change	Treatment	Treatment
Treatment Store 3	no change	no change	Treatment
Treatment Store 4	no change	no change	Treatment

Our labelling and analysis focuses on 20 core models which capture 95.3% of retail sales during the trial period (see Table B.1 (Appendix B) for a description of these models). The remaining 4.7% of sales are made up of 46 models which do not regularly feature in the standard retail lineup; for example, they were available only on order. We had to exclude these models because the retailer's sales system does not differentiate between non-sale and non-availability at the store level (both show as zeros in the data). This implies that a singular sale in only one store automatically generates zero observations across the remaining stores, many of which may not have stocked the relevant model.

The consumption labels were designed in conjunction with retail management and the initial labelling application was carried out by the authors and store management/staff. Consumption costs are based on an aggregate annual load of 800kg, which is consistent with the levels adopted in recent dryer labelling regulations (European Commission, 2012). Furthermore, we assume that the price of energy remains fixed at €0.19/kWh (average residential price in Ireland in January 2013) and we also omit a discount rate. These exclusions, while lowering the precision of the forecasts, were, we believe, necessary to improve the clarity and interpretability of the labels (which included all of our calculation

assumptions).[29] These estimates are, however, intended to provide a general energy cost guide only, which buyers can then adjust according to their own expected use and price expectations. These assumptions, in combination with each manufacturer's stated kWh/cycle (based on a full load of cotton spun at 1000 rpm) and capacity (load size), gives each model's energy cost. For appliance m with capacity C, kWh per cycle e and lifetime T, this is therefore:

$$X_m = \frac{Q}{C_m} * e_m * P * T_m \tag{2}$$

where Q and P are annual load and electricity price respectively.[30] This monetary information, together with our assumptions, was displayed in a prominent position on the front of each machine in each of the treatment stores for the duration of the trial (see Figure 3.1 for labelling example). We also displayed the number of weekly loads (differed due to capacity) in addition to the aggregate annual load assumed, as we expected this format would be more intuitive for potential buyers.

[29] The concept of discounting is unlikely to be understood by the general public and it was excluded as it could have lowered the clarity of the labels and therefore buyer engagement (and possibly sales staff engagement). Furthermore, while buyers are more likely to understand energy price inflation, it was also excluded in the interest of transparency. However, on aggregate, the combined exclusion of these two factors, one of which has an upward push on future energy cost (inflation) and one which has a downward (discounting), is likely to be less biasing.

[30] For example, an 8KG dryer with a kWh/cycle rating of 5.12 will have a five year energy cost of $\frac{800}{8} * 5.12 * €0.19 * 5 = €486.40$

Figure 3.1: Five Year Energy Cost Label (example)



In addition to energy consumption, further dryer attributes were collected from the company's website. These are attributes assumed to be valued by buyers, and include the presence of a timer, a large opening, a drying sensor, a delay timer and reverse action. Furthermore, information on price (common to all stores) and dryer type (vented or condenser) is available (Table 3.2).

Table 3.2: Descriptive Statistics for Dryer Sales

	Mean	Std. Dev.	Min.	Max.
kWh/annum	466.20	57.57	210	538
kWh/cycle	4.37	0.70	1.9	5.76
Price	296.36	99.32	179.99	699.99
Timer [D]	0.35	0.48	0	1
Large Opening [D]	0.41	0.49	0	1
Drying Sensor [D]	0.35	0.48	0	1
Reverse Action [D]	0.14	0.35	0	1
Vented [D]	0.28	0.45	0	1

Note: 'D' stands for dummy variable. Descriptive Statistics are based on all time periods (P0, P1 and P2)

Descriptive statistics for store area demographics are presented in Table B.2 (Appendix B), and some noticeable differences between treatment stores and the population are apparent.[31] Firstly, in terms of education, the proportion with an honours degree (or above) is higher than the population (24% for all treatment stores compared to 17% in the State). For unemployment, treatment store shares (11% combined) are similar to national figures (12%). Similar findings are evident for social classes, with treatment stores (combined) showing very similar shares relative to national figures.

3.3 Methods

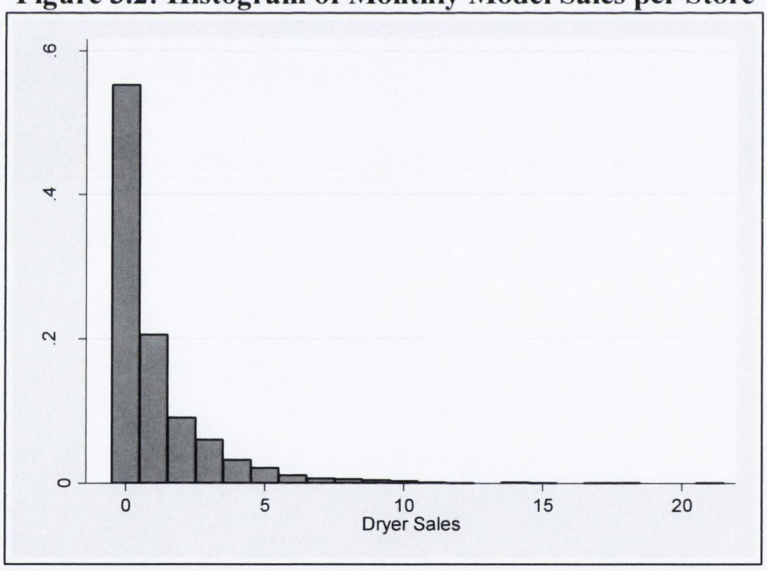
We are interested in the factors that influence dryer sales within the retail space. Dryers are not impulse purchases and the decision to buy is likely due to either breakdowns, a move to a new property or refurbishment of an existing one. The product attributes and the consumption information provided are unlikely to have a significant influence on market participation (whether or not to buy any dryer), but will affect the choice of dryer once the buyer enters the store. In any event, we do not have access to data on what might inform a

[31] These are downloaded from www.cso.ie (Census of Population, 2011)

regression of the decision to buy a new dryer *per* se. Instead, we estimate the number of units of a model purchased by customers in a given store during a given month. Our results are implicitly conditional on the decision to buy a dryer having already been made, so we do not take account of any effect labelling or other factors might have to deter, delay or encourage dryer purchases in general.

To allow for the high proportion of zero observations in the dependent variable (55% - see Figure 3.2) we employ a count regression (negative binomial model). The implicit assumption here is that zeros in the data are generated by the same process as positive numbers of units purchased. A zero represents a case in which no units of a given dryer model were purchased in a particular store in a month. It does not necessarily represent a decision by a customer not to buy at all.

Figure 3.2: Histogram of Monthly Model Sales per Store



The starting point for the negative binomial model is the Poisson model (the econometric methodology presented here follows Cameron and Trivedi (2010) and Greene (2008)). The model assumes that each observation (count) is drawn from the Poisson distribution:

$$\text{Prob}(Y = y_i|\boldsymbol{x}_i) = \frac{e^{-\mu_i}\mu_i{}^{y_i}}{y_i!}, \qquad y_i = 0,1,2,3, \ldots \tag{3}$$

The standard parameterisation is $\ln \mu_i = \boldsymbol{x}'_i\beta$, and the expected number of events per period equals:

$$E[y_i|\boldsymbol{x}_i] = Var[y_i|\boldsymbol{x}_i] = \mu_i = \exp(\boldsymbol{x}'_i\beta) \tag{4}$$

This highlights the main drawback of the Poisson model – the distribution implies equal mean and variance (equidispersion), which is not the case in the current application (Figure 2). To allow for the variance and mean to differ (overdispersion), the model is extended to account for unobserved heterogeneity by replacing μ_i with $\mu_i v_i$, where v_i follows a gamma distribution (with mean equal to one and variance parameter α). The negative binomial distribution is denoted by:

$$\text{Prob}(Y = y_i|\boldsymbol{x}_i, \alpha) = \frac{\Gamma(\alpha^{-1}+y_i)}{\Gamma(\alpha^{-1})\Gamma(y_i+1)}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu_i}\right)^{\alpha^{-1}}\left(\frac{\mu_i}{\mu_i+\alpha^{-1}}\right)^{y_i} \tag{5}$$

where $\Gamma(\cdot)$ denotes the gamma integral that specialises to a factorial for an integer argument (Cameron and Trivedi, 2010). The parameter α captures the degree of overdispersion and reduces to the Poisson model when equal to zero. The expected mean and variance for the above are:

$$E[y_i|\boldsymbol{x}_i] = \mu_i = \exp(\boldsymbol{x}'_i\beta) \tag{6a}$$

$$Var[y_i|\boldsymbol{x}_i, \alpha] = \mu_i(1 + \alpha\mu_i) \tag{6b}$$

The effects of treatment are estimated using a difference-in-difference-type approach while controlling for other product attributes. An exposure variable (z) is included to control for differences in observational settings. For example, the number of sales of a particular model must account for the number of potential customers passing through: $E[y_i|\boldsymbol{x}_i] = \text{z} * \exp(\boldsymbol{x}'_i\beta)$. For this, we use each store's total monthly sales as a proxy. Equation 6a (expected sales of model m in store j during month t) is then:

$$\mu_{mjt} = \exp[\beta_0 + \beta_1 w_t + \beta_2 e_m + \beta_3 z_j + \beta_4 (w_t * e_m) + \beta_5 (w_t * z_j) + \beta_6 (e_m * z_j) +$$

$$\beta_7 (w_t * e_m * z_j) + \sum_1^r \beta_{r+7} N_m r + \ln(\text{exposure}_{jt})] \quad (7)$$

where
w: trial period dummy
e: efficiency rating (kWh/annum)
z: treatment dummy
N: dryer characteristics

Our main interest is the relationship between model efficiency and sales. In this regard, β_2 describes the effect for the control group pre-trial (P0) and β_4 shows if there is a significant change during the trial period (P2). The coefficient for the three-way interaction coefficient (β_7) describes any additional change for the treatment group during the trial. We would expect a negative relationship between efficiency (kWh per annum) and sales (a negative and significant β_2) holding all other product characteristics constant. If treatment increases the value that buyers place on energy efficiency, the magnitude of this relationship will increase (β_7 also negative and significant).

3.4 Results

In order to capture the aggregate treatment effect (all four stores) the analysis focuses on March-April (P0: pre-trial period) and August-October (P2: trial period). A number of descriptive results are worth noting prior to analysis. The mean efficiency of dryer sales across treatment and control groups pre/post-trial is displayed in Table 3.3. First, there appears to be no difference in mean kWh/annum between control and treatment groups pre-trial (both are about 470 kWh). Furthermore, while the mean kWh/annum for the control group decreased by 0.4% during the trial (P2 compared to P0), the reduction for treatment stores is larger (3.4%), and appears to be primarily driven by reductions in Store

1 and Store 3. Mean kWh/cycle has, however, increased for control stores during the trial (5.6% higher than P0).[32] Although this is also observed for treatment stores, the increase is lower (2.3%).

Table 3.3: Average Efficiency of Dryers Sales

	P0 (Mar – April)		P1 (May – July)		P2(Aug – Oct)	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
kWh/annum:						
Control Stores	470.067	40.748	466.402	49.717	468.263	61.981
Treatment Store 1	468.348	30.997	455.824	63.455	447.590	86.309
Treatment Store 2	483.143	32.320	473.451	76.165	478.440	47.781
Treatment Store 3	466.751	29.167	464.460	27.834	446.271	77.983
Treatment Store 4	475.414	30.891	448.702	92.131	460.447	73.836
Treatment Stores	470.387	30.687	461.783	64.664	454.401	76.560
kWh/cycle:						
Control Stores	4.237	0.696	4.338	0.730	4.475	0.665
Treatment Store 1	4.134	0.608	4.325	0.777	4.346	0.856
Treatment Store 2	4.542	0.710	4.557	0.908	4.581	0.528
Treatment Store 3	4.286	0.542	4.390	0.452	4.265	0.736
Treatment Store 4	4.137	0.517	4.030	0.861	4.282	0.782
Treatment Stores	4.245	0.598	4.349	0.754	4.345	0.759

Note: Shaded areas indicate trial period

Results from the negative binomial model are displayed in Table 3.4.[33] 'Model 1' presents results without the efficiency interactions while 'Model 2' displays the full results. The α parameter is positive and significant in both, confirming that the data are over-dispersed (rejecting the standard Poisson distribution). Table 3.5 displays the predicted probabilities (number of sales) for Model 2. It is apparent that these probabilities are close to the actual

[32] This is likely driven by an increase in mean capacity between surveys, which was 7.2KG in P0 and 7.7 in P2

[33] A noteworthy data issue arose during the experiment: during the pre-trial period, the retailer launched a new A-rated dryer which was rolled out during the first two months (the dryer was available in treatment and control groups during the trial period). While this unit was available in treatment stores pre-trial (Stores 1 and 2), we have no data on its general availability across the control group during the pre-trial period. To preclude the possibility that its presence may have influenced the results, we ran a robustness check in which we replaced these units with missing observations (in place of zeros) for the control group in the pre-trial period. This test has no significant effect on the results (treatment effects remain insignificant).

sample shares (although the predicted number of ones is about 10% higher), suggesting that the specification fits the data very well.

The coefficients show the effect of a one unit increase in the independent variable on the log of a model's sales (approximately equal to the percentage change). Dryer sales, as expected, are significantly reduced by price increases, and a one unit (euro) increase in price is associated with a 1.5% reduction in model sales. A number of other dryer attributes are positive and significant, including the presence of a large opening (30% increase) and a timer (doubles sales). The remaining attributes (drying sensor and reverse action), while positive, are insignificant. Furthermore, the demand for vented dryers is significantly lower.

In Model 2, the negative sign on efficiency implies that, holding all other factors constant, higher efficiency (lower kWh/annum) reduces dryer sales in P0 (for control stores pre-trial).[34] However, this variable is not significant, suggesting that this is not an important attribute. Furthermore, this relationship has not significantly changed for control stores during the trial period (efficiency-trial interaction insignificant). Also, the three-way interaction, while of the expected sign (negative, and suggesting that treatment increased demand for efficiency), is not significant.

As the presence of interactions complicates the interpretation of magnitude, marginal effects (predicted number of counts/sales) are estimated for control and treatment stores during the trial period for all possible efficiency levels (presented in Table 3.6). It is apparent that differences between control and treatment group sales are larger for higher levels of efficiency (lower kWh/annum levels) – for example, while sales of 475 kWh dryers (close to mean kWh for the sample) are 28% higher in treatment stores (versus

[34] For Model 1, this variable highlights the overall effect of energy efficiency for both groups (control and treatment) and periods (P0 and P2).

control stores), sales of 275 kWh dryers are about twice as high. However, these differences are only statistically significant for less efficient dryers (above 300kWh) and sales of the most efficient dryers (275 kWh and below) are not significantly higher in the treatment group (which is expected given the insignificant three-way interaction).

Table 3.4: Negative Binomial Model Results

	Model 1			*Model 2*		
	Coef.	**Std. Err.**	**P>|z|**	**Coef.**	**Std. Err.**	**P>|z|**
Price	-0.015***	0.003	0.000	-0.015***	0.003	0.000
Price squared	0.000	0.000	0.274	0.000	0.000	0.168
Vented [D]	-1.843***	0.147	0.000	-1.791***	0.147	0.000
Timer [D]	1.000***	0.125	0.000	0.945***	0.127	0.000
Large Opening [D]	0.303***	0.107	0.005	0.303***	0.107	0.005
Drying Sensor [D]	0.098	0.139	0.482	0.170	0.141	0.230
Reverse Action [D]	0.014	0.136	0.920	0.066	0.140	0.639
e (efficiency)	-0.005**	0.002	0.017	-0.003	0.002	0.248
z (treatment) [D]	-	-	-	-0.534	1.240	0.667
w (trial period) [D]	-	-	-	0.487	0.643	0.449
e * z	-	-	-	0.001	0.003	0.611
e * w	-	-	-	-0.001	0.001	0.291
z * w	-	-	-	1.651	1.401	0.239
e * z * w	-	-	-	-0.004	0.003	0.211
Constant	3.645***	0.999	0.000	2.701**	1.115	0.015
α	1.121	0.084	0.000	1.098	0.082	0.000
N	1620			1620		
Log Likelihood	-2267.110			-2260.670		
Wald χ^2 statistic	278.310			291.180		
Prob $\geq \chi^2$	0.000			0.000		

Note: All model are estimated in STATA version 13 ('nbreg' command). [D] indicates dummy variable, '' significance at 1%, '**' at 5% and '*' at 10%. Store monthly sales are used for the exposure variable. The Wald statistic is for a likelihood ratio test of the joint significance of the regressors.***

Table 3.5: Model Predicted Probabilities and Sample Proportions

	Predicted (P)	Std. Dev	Sample Shares (S)	Difference (S-P)	Ratio (S/P)
Prob.(y=0)	0.527	0.191	0.536	0.008	0.984
Prob.(y=1)	0.207	0.039	0.188	-0.018	1.098
Prob.(y=2)	0.101	0.040	0.094	-0.006	1.068
Prob.(y=3)	0.056	0.034	0.065	0.009	0.862
Prob.(y=4)	0.034	0.026	0.038	0.005	0.878
Prob.(y=5)	0.021	0.021	0.025	0.003	0.869
Prob.(y=6)	0.014	0.016	0.015	0.001	0.931
Prob.(y=7)	0.010	0.013	0.011	0.001	0.944
Prob.(y=8)	0.007	0.010	0.007	0.000	0.952
Prob.(y=9)	0.005	0.008	0.007	0.002	0.753
Prob.(y=10)	0.004	0.007	0.005	0.001	0.775

Note: Predicted probabilities are estimated using the 'prcounts' command in STATA (Long and Freese, 2001). This estimates the probabilities for each observation and then calculates the overall mean.

Table 3.6: Predicted Counts (Monthly Sales) for Treatment and Control by Efficiency (kWh/cycle) for Trial Period

	Control Stores			Treatment Stores			Wald Test H_o: Control (C) - Treatment (T) = 0		
kWh/annum	**Counts (C)**	**Std. Err.**	**P>|z|**	**Counts (T)**	**Std. Err.**	**P>|z|**	**T – C**	**chi-squared value**	**Prob. > chi-squared**
200	3.740	2.293	0.103	9.335	6.271	0.137	5.595	1.520	0.218
225	3.363	1.879	0.074	7.904	4.838	0.102	4.540	1.750	0.186
250	3.025	1.526	0.047	6.692	3.698	0.070	3.667	2.030	0.154
275	2.720	1.224	0.026	5.666	2.795	0.043	2.946	2.400	0.122
300	2.446	0.968	0.012	4.797	2.084	0.021	2.351	2.860*	0.091
325	2.200	0.752	0.003	4.061	1.527	0.008	1.861	3.470*	0.063
350	1.978	0.570	0.001	3.439	1.094	0.002	1.460	4.270**	0.039
375	1.779	0.417	0.000	2.911	0.761	0.000	1.132	5.280**	0.022
400	1.600	0.291	0.000	2.465	0.511	0.000	0.865	6.420**	0.011
425	1.439	0.188	0.000	2.087	0.328	0.000	0.648	7.190*	0.007
450	1.294	0.109	0.000	1.767	0.208	0.000	0.473	6.530**	0.011
475	1.164	0.064	0.000	1.496	0.151	0.000	0.332	4.300**	0.038
500	1.047	0.074	0.000	1.267	0.150	0.000	0.220	2.060	0.151

Note: Counts estimated for covariates at sample means during the trial period. Standard errors estimated using the delta method (within STATA's 'margins' command). A Wald test ('test' command) is used for comparing treatment and control group predicted counts. Actual counts have been scaled to conceal commercial information.

3.5 Discussion

Current EU labelling, while providing a relative efficiency guide, falls short of giving buyers an energy cost forecast, and there is evidence from previous research (Heinzle, 2012) that many households may not be able to convert the available quantitative energy information (kWh per cycle/annum, for example) into such. Furthermore, to calculate an appliance energy forecast, households must also be aware and have expectations of energy prices and their expected levels of use. It is therefore possible that specific long-term monetary energy cost information is missing from the appliance investment decision. From a policy perspective, the question is whether this specific information gap is reducing the adoption of more efficient technologies, or if current EU labels, based on non-monetary quantitative and qualitative appliance comparisons, are adequately informing households of their future energy consumption.

The results of this paper do not, however, support the hypothesis that this information gap is reducing the uptake of more efficient appliances – while mean efficiency has improved in treatment stores (3% reduction in mean kWh/annum consumption), the regression analysis does not show the increase in demand for higher levels of energy efficiency to be significant. However, it is possible that our results are at the lower end – our energy consumption labels are based on a short five-year lifetime and do not account for energy price inflation. In this regard, the stated preference analysis of Heinzle (2012) demonstrates that the duration of the forecast matters – the longer the lifetime, the larger the energy cost forecast, and this results in a larger willingness-to-pay for efficiency improvements (she also shows that a one year forecast in fact has a *negative* effect). It is also possible that the insignificance of our results are driven by the short duration of the trial (three months).

From a policy perspective, supplying 'lifetime' energy cost information would be a relatively straightforward and inexpensive addition to current labelling requirements. In addition, heterogeneous consumers could be provided with personalised cost forecasts through information technology (in store applications/installations, for example, which account for a buyer's expectations on level of use, product lifetime and energy prices). However, given our own findings and the mixed results in previous research, we suggest that further trials are carried out on different products, cost forecast durations and jurisdictions. For example, the effects of lifetime labelling are likely to be heterogeneous across appliance groups and will depend on the size and variance of energy consumption levels (Sallee, 2013). In this regard, previous studies (see Kallbekken et al. (2013) and DEEC (2014)) show that lifetime labelling has a significant effect on some appliances but not on others. It is also possible that lifetime labels could even have a negative effect on the demand for energy efficiency when, for example, energy costs are significantly below buyer expectations. In addition, as the labels used in previous trials are new and unfamiliar to buyers, the behavioural effects could be diminished. If lifetime labels were incorporated into current EU labelling policy, it is possible that the EU label design, accreditation and accompanying marketing campaigns would lead to higher levels of consumer engagement.

There is clearly scope for further consumer trials. Studies exploring the effects of lifetime labels on appliance size decisions could also be of particular interest. For example, while buying a smaller dryer or washing machine will not reduce a household's energy costs (assuming no scale-efficiency effects and appliances are used to their capacity), reducing the size of products such as fridges or TVs would. To illustrate, the kWh/annum rating of different sized fridges within the 'A+' band varies between 183 kWh and 417 kWh (EU labels).[35] Therefore, EU efficiency bands, while promoting efficiency for a fixed unit of size, may not communicate the conservational effects of size reductions. For example,

[35] Based on website information of one retailer (accessed April 29th, 2014)

were 5-year consumption cost labels, as presented in this paper, also displayed on these fridges, the costs would range from €174 - €396, despite the fact that they are all within the same 'A+' category. Households therefore may respond to lifetime energy costs by either improving efficiency or reducing size, or both. Furthermore, for households that cannot afford the most efficient technologies (or have no access to financing), lifetime energy costs highlight an additional route to reduce their energy costs.

3.6 Conclusion

The energy efficiency gap describes the degree to which households fail to minimise the total cost of their investments. Over the lifetime of the investment, misoptimisation has private welfare-reducing implications through lower non-energy consumption. On aggregate, misoptimisation will lead to a stock of appliances which over-consume (relative to the hypothetical 'optimal'), implying increased electricity generation and environmental impacts.

Previous research suggests that specific monetary energy cost information is missing from the appliance investment decision. This paper explores whether this omission is reducing the demand for energy efficiency by displaying lifetime consumption costs within a retail experiment (in addition to current EU labels). While the descriptive results show an improvement in mean efficiency in treatment stores (3% reduction in kWh/annum), the regression analysis demonstrates that the demand for energy efficiency, while improved, is not statistically significant. However, our trial was subject to a number of design constraints that could limit the external validity of the results. Furthermore, mixed results from previous research suggest that further trials would be required before lifetime energy costs are incorporated into labelling policy.

Chapter 4

Low Efficiency in Residential Rental Properties: Asymmetric Information or Low Willingness-to-Pay?

4.1 Introduction

4.1.1 Background: the owner-renter efficiency divide

Rental markets play an important role in meeting housing needs. In the US, the share of rental households was 35% in 2012, up from 31% in 2004 (Joint Center For Housing Studies of Harvard University, 2013). In the EU, 29% of the population live in rented properties, with proportions as high as 36% in France and 47% in Germany (Eurostat, 2014). Understanding the structural efficiency of these properties and the energy-related decision-making of occupants is therefore important for forecasting the rental market's potential contribution towards energy reducing targets and climate change mitigation in general. Furthermore, highlighting differences in rental efficiency is relevant from private welfare and equity perspectives. Renters tend to be at an earlier stage in their career and have lower income levels.[36] Low energy efficiency negatively affects immediate welfare through higher energy expenditure (and/or lower thermal comfort) and possibly microeconomic development through reduced savings.

Internationally, there is a clear owner-renter energy efficiency divide. For example, in the US, just 17% of rented properties have weather stripping (compared to 45% of owner-

[36] In the 2004-2005 Irish Household Budget Survey (HBS), the mean age and disposable income of renters is 42 years and €32,446 while 54 years and €45,182 for owners (author's calculations). HBS data is available by application to The Irish Social Science Data Archive at www.ucd.ie/issda/issda

occupied), 43% have double-glazing (compared to 63%) and, overall, just 28% of rented properties are considered 'well insulated' (compared to 40%) (U.S. Energy Information Administration, 2013).[37] The percentage of renters with *Energy Star* fridges, washing machines and dishwashers is also low (23%, 11% and 6% respectively, compared to 44%, 31% and 27% for owners). Davis (2012) also finds similar appliance differences after controlling for a large number of occupant characteristics, climate conditions and locations.[38] Interestingly, he also finds the more mobile the appliance (air conditioning units and light bulbs, for example) the lower the divide. Also in the U.S. (California), Gillingham et al. (2012) find that renters are 20 percent less likely to have attic and ceiling insulation and 13 percent less likely to have exterior wall insulation (again, controlling for household characteristics). In the UK, similar differences are observed, with renters showing lower levels of double glazing (71% versus 75% for owner-occupiers), attic insulation (25% versus 46%) and cavity wall insulation (21% versus 40%) (Department for Communities and Local Government, 2013).[39] In the Netherlands, private renters again show lower levels of attic and wall insulation and efficient glazing (40%, 29% and 48% respectively) than owner-occupiers (70%, 52% and 70%) (IEA, 2007 pg. 133). Also, in Australia, 28% of renters have no attic insulation compared to 6% owner-occupiers and have less efficient space and water heating systems (Burfurd et al., 2012).

In Ireland, where the analysis of this paper is focused, a large and representative housing quality survey (40,000 properties in 2001) explored the presence of a number of energy-saving items, including wall and attic insulation, double-glazing, draft stripping, energy-saving lighting and automatic controls for central heating and water (ESRI, 2003). It is found that renters, in general, have lower numbers of these items (as do adults living alone, older properties and households with the lowest income). The presence of wall and attic

[37] Author's calculations using 2009 *Residential Energy Consumption Survey* (RECS) data (downloaded from the U.S. Energy Information Administration).
[38] Using 2005 RECS data
[39] Attic insulation figures refer to levels of 150mm or above.

insulation in older privately rented properties (pre 1940) is particularly low.[40] Using this same data, O'Doherty et al. (2008) show that the number of energy-saving installations is 10.4% and 21.2% lower for local authority and private renters respectively.

4.1.2 Theoretical background: understanding the divide

Standard microeconomic theory provides a much cited explanation of low energy efficiency levels in rental properties. Many efficiency improvements, such as increased wall insulation or high efficiency windows, are generally irreversible and non-mobile investments, and would typically have a payback period longer than most rental leases. It is therefore, in general, only feasible for the landlord (rather than the renter) to invest in energy efficiency. A cost-minimizing renter will, however, consider rented properties with increased efficiency as long as the expected marginal energy savings outweigh the rent increases (holding all other property attributes fixed). Similarly, the profit-maximising landlord will invest in energy efficiency until the expected discounted marginal increase in future rents equals the cost of capital.

Asymmetric information, however, creates a principal-agent problem which may explain sub-optimal energy efficiency standards in the rental market (see, for example, Jaffe and Stavins (1994b), Murtishaw and Sathaye (2006), IEA (2007), Davis (2012) and Allcott and Greenstone (2012)). Some energy-related technologies, such as wall and attic insulation, are unobservable to prospective tenants, and this information is costly to acquire (hiring an independent assessor, for example). Even with seemingly observable technologies, such as efficient windows and appliances, the specific thermal and energy-intensity information required to form energy and cost expectations may only be available to landlords (acquired

[40] For example, for older houses, only 19% of private renters had wall insulation while 42% had roof insulation (compared to 53% and 78% for mortgage holders and 36% and 58% for those who own outright).

at the point of sale). As is the usual outcome in any market with uncertain quality (Akerlof, 1970), there is adverse selection and the market can fail – tenants will assume an average efficiency level and will fail to choose properties which minimize their energy costs, and landlords, knowing that increases in efficiency are not rewarded by increased rents, will have no incentive to invest.

4.1.3 Research question: do renters value energy efficiency?

This explanation of the problem offers policymakers a straightforward means of correcting the market failure by directly removing the informational asymmetry through the provision of property efficiency labelling. For example, in Ireland, the *Building Energy Rating* (BER) combines all efficiency attributes (space/water heating, ventilation and lighting) into a single figure (kWh/m^2/annum) presented on a categorical scale (see Appendix C, Figure C.1). The policy is similar to the UK's *Energy Performance Certificates* (EPC) and the *Leadership in Energy and Environmental Design* (LEED) certification in the USA.

However, the market failure, as described, and, indeed, this corrective policy intervention, rests upon a number of key underlying behavioural assumptions. First, that renters are attentive to their energy costs and/or environmental impact, second, that they are willing to pay more for higher levels of energy efficiency and, third, that the marginal willingness-to-pay for efficiency upgrades equals or exceeds the marginal cost for the landlord. If any of these assumptions are not present, correcting the asymmetric information problem will not reduce the efficiency divide. Our core research question therefore explores these underlying renter motivations and asks – in a perfectly informed rental market, what is the willingness-to-pay for energy efficiency?

Although there is a sizable literature exploring the effects of energy ratings for property sales (see, for example, Hyland et al. (2013) Kok and Kahn (2012), Bloom et al. (2011), Brounen and Kok (2011) and Heinzle et al. (2013)), the rental market, being of smaller size, is less examined. The available studies do, however, show a significant and positive relationship between rents and energy efficiency ratings.[41] For example, Cajias and Piazolo (2012) show that a one percent increase in energy consumption (a decline in efficiency) leads to a 0.075% decline in rents in Germany. Furthermore, in a detailed multi-region analysis, European Commission (DG Energy) (2013), find that energy efficiency improvements are associated with a 4.4% rent increase in Austria (for a one letter improvement – D to C, for example) and a 3.2% increase in Belgium (for a 100 CPEB point increase).[42] Previous research in Ireland (Hyland et al., 2013) also finds a positive effects between efficiency and rents using listings from Ireland's largest online rental website (daft.ie).[43] Using the BER, they find that each increase in rating raises rents by 0.5%, or by €5 (given the average monthly rent in the sample of €1005).[44] There are, however, a number of inconsistencies evident in this Irish rental market dataset: for example, rents in 'A' rated properties (the highest efficiency point on the scale) are lower than 'B' rated and 'C' receives the same rents as 'D'.

This paper differs to previous studies in that we employ a stated preference technique – a Discrete Choice Experiment (DCE) – to explore the willingness-to-pay for energy efficiency. The next section discusses our empirical approach and the advantages (and disadvantage) of using a hypothetical experiment over a more traditional revealed preference analysis, given the current market conditions. Section 4.3 presents our

[41] For the commercial rental sector, European Commission (DG Energy) (2013) provides a detailed summary of the effects of rental labels. With few exceptions (one of ten studies), there is a significant rental premium attached to energy ratings, in the region of 2 to 6% (and as high as 15%).
[42] The CPEB score gives the property's energy rating and ranges from low values (less than 150) associated with poor efficiency to high values above 600 for the most efficient.
[43] European Commission (DG Energy) (2013) used these data also.
[44] Controls include location (county), dwelling type, number of bedroom/bathrooms, appliances (including cable TV, dishwasher and microwave) and the presence of a garden and parking.

regression results plus some notable survey responses. A discussion and conclusion follow in sections 4.4 and 4.5 respectively.

4.2 Method: A Discrete Choice Experiment of Renters

4.2.1 Background and empirical motivation

DCEs are used to measure a decision unit's valuation of a good or service where revealed preference data are unavailable, for example, for non-market services, new commercial goods or for testing new policies in existing markets (see Hensher et al. (2005) for an introduction). In the survey, hypothetical choice situations, based on a controlled and bounded set of attributes, are presented to a sample of likely market participants. Attribute levels and respondent choices are then used to estimate marginal willingness-to-pay (for attributes) and marginal rates of substitution (between attributes). The approach has been used in numerous sectors, including health (see Ryan and Gerard (2003), for example), transport (Greene and Hensher, 2003) and environmental evaluation (Hanley et al., 1998). Within energy-related research, DCEs have been employed for valuing appliances (Revelt and Train, 1998), renewable generation (Bergmann et al., 2006), household energy-saving technologies (Banfi et al., 2008), micro-generation (Scarpa and Willis, 2010) and electric cars (Hidrue et al., 2011).

In the current setting we present respondents with apartment choices which differ according to a number of property attributes, including energy efficiency. For the latter, we use the current informational policy in Ireland – the BER. We employ a stated preference technique as the current rating system, although a legal requirement for landlords, is showing very low levels of compliance, and non-disclosure, both in advertisements and

during negotiations, is commonplace.[45] For example, a simple manual search on daft.ie reveals that around two thirds of advertisements do not include a BER rating.[46] This proportion is similar to official national BER records (28%) and would therefore suggest that non-advertisement is largely due to non-certification (failure of landlords to commission certification).[47] However, the proportion of certified rental properties is currently unknown, and it is also possible that non-disclosure is due to deliberate attempts to withhold poor efficiency information. In this regard, recent advertisement data from daft.ie presents some evidence of misinformation in landlord-tenant negotiations. For example, while 25% of rated properties have low efficiency levels ('E', 'F' or 'G') (official nation data), just 10% of properties advertised on daft.ie are in this category (Table 4.1). Furthermore, the advertised data also shows an overrepresentation of 'A' rated properties (10%), with stark differences compared to national statistics (less than 1%). Also, these proportions do not show the owner-renter efficiency divide which is present in Ireland (even allowing for a smaller divide in Table 4.1 due to the inclusion of rented properties in official BER figures).

Table 4.1: BER shares nationally (owner plus rented) and in rental markets (advertised)

	National BER shares	Advertised BER shares
A	0.73%	10.52%
B	12.70%	23.72%
C	36.22%	37.83%
D	25.28%	17.57%
E	12.31%	6.91%
F or G	12.76%	3.45%

Note: National BER shares are calculated using data from the SEAI National BER Research Tool (accessed July 2014 and available at www.seai.ie) and advertised BER shares are based on daft.ie rental data, highlighted in Hyland et al. (2013).

[45] Since January 2009, all properties sold or rented are required to have completed BER certification. Since January 2013, it is also illegal to advertise a property without a BER certificate.

[46] Based on 100 property advertisements (first 100) in Dublin city on daft.ie with rents between €800 and €1400 and with one to three bedrooms (searched on 4th July 2014).

[47] National BER records downloadable from www.seai.ie/Your_Building/BER/National_BER_Research_Tool/ [accessed July 4th, 2014]

DCEs also allow us to re-create a realistic rental choice situation by including very specific and valued property attributes (highlighted in our focus group) which are not readily available in revealed preference data (condition or area safety, for example). Furthermore, through experimental design, we can isolate the independent effects of each attribute; a task which can be problematic in revealed preference analysis when independent variables are often correlated with each other, or with the error term – for example, if a property's condition is unknown but correlated with energy efficiency, the relationship between efficiency and choice will be biased upwards (provided condition is valued). Finally, the method offers us full control of the experimental setting, thus enabling us to estimate the likely future effects of the BER policy (when compliance and disclosure is universal).

The hypothetical nature of choice experiments has, however, received criticism in the literature. While much of this has been directed towards the contingent valuation method (CVM) (see Diamond and Hausman (1994) Kling et al. (2012) Hausman (2012)), the possibility of 'hypothetical bias' in choice experiments is also an obvious concern. However, for CVM, some studies have found (see Carson et al. (1996), for example) that WTP estimates are in fact a useful predictor of actual valuation, although, on average, are slightly below.[48] For choice experiments (see Carlsson (2011)), there are also studies which find no bias in marginal WTP estimates (Carlsson and Martinsson (2001) and Lusk and Schroeder (2004)).[49] There are also, of course, studies which find the opposite (Johansson-Stenman and Svedsäter, 2008).

There are some more practical issues in choice experiments which could lead to biases in estimates. These are discussed for laboratory experiments by Carlsson (2011), but are equally relevant for this applied methodology. For example, experiments are normally

[48] Carlsson (2011) provides a summary of studies exploring these biases (pg. 204), in the CVM, choice experiment and experimental settings.
[49] Lusk and Schroeder (2004) do, however, find that hypothetical responses overestimate *total* WTP.

conducted out of context, and respondents are asked to choose a good in a setting that is unfamiliar to where the transaction normally takes place. Second, it is possible that respondents may adjust their behaviour as they feel their choices are under scrutiny. Finally, the presented alternatives may not resemble real-life choice sets, as they are clearly defined and normally restricted to two or three (when actual choice sets can be vast and decisions are often made with imperfect information). Such simplicity and clarity of attributes may lead to biases in hypothetical decision-making, relative to the real-world. However, biases and drawbacks withstanding, the main motivation for conducting stated preference surveys remains – the unavailability of revealed preference data – and in this respect, choice experiments are one of the few viable methods available. The challenge for the researcher is to ensure that the situation presented resembles a real-life choice situation, is noncomplex and clearly understood by the respondent.

4.2.2 Theoretical model and econometric method

The total cost of renting a property equals the sum of rent and auxiliary costs. The rent is a function of the property's attributes, including, for example, location, size and structural finish. Although there are many potential auxiliary costs – telephone, waste and water charges, for example – we will consider energy costs only. For the prospective renter then, the expected total cost for a property then equals:

$$E[C_{m,i}] = R_m(\boldsymbol{X}^*_{\boldsymbol{m}}, e_m) + E[P_E * I_i(e_m)] \quad (1)$$

where $C_{m,i}$ is the cost of property m (from a set of M properties) for individual i, R_m is the rent, $\boldsymbol{X}^*_{\boldsymbol{m}}$ is a vector of k property attributes (excluding the efficiency level), P_E is the price of energy and I_i is the quantity of energy units consumed. Both the rent and auxiliary costs

are a function of the property's energy efficiency level (e_m), positively and negatively respectively. The energy efficiency level of the property is a function of the level and quality of wall and attic insulation, window glazing, the space and water heating technologies installed and the efficiency of installed appliances.[50]

The rental choice problem can be presented within a more general utility maximization problem (see Alpízar et al. (2001), Hensher et al. (2005), for example):

$$\max_{Z,m\in M} U_i(Z, \boldsymbol{X_m}) \quad s.t. \;\; Z \leq Y_i - R_m \tag{2}$$

where $U_i(.)$ is the utility function of individual i, Z is a vector of consumer goods (with price vector P_z *normalized to 1*) and Y_i is income. The individual will choose property m if:

$$V_{im}(\boldsymbol{X_m}, Y_i - R_m) > V_{in}(\boldsymbol{X_n}, Y_i - R_n) \qquad \forall n \in M; n \neq m \tag{3}$$

where $V(.)$ is the indirect utility function. Assuming that utility is a linear additive function of property attributes, and allowing for a random noise term for measurement error, unobserved individual characteristics, missing attributes and/or heterogeneity of preferences, the utility associated with property m for individual i is then:

$$U_{im} = \boldsymbol{\beta'} \boldsymbol{X_m} + \gamma(Y_i - R_m) + \varepsilon_{im} \tag{4}$$

where β is the coefficient vector (marginal utilities of attributes), γ is the marginal utility of income and ε_{im} is an unknown individual/alternative specific noise term. The marginal willingness-to-pay (MWTP) for an attribute then equals the marginal rate of substitution (MRS) between the attribute and money:

$$MWTP = \frac{-\partial U_{im}/\partial x_{km}}{-\partial U_{im}/\partial Y_i} = -\frac{\beta_{km}}{\gamma} \tag{5}$$

[50] Installed appliances refer to any appliance that came with the property.

where x_{km} is the k[th] element of attribute vector $\boldsymbol{X_m}$, and β_{km} it's coefficient. Overall, the probability of choosing property m equals[51]:

$$P(m: M, \beta, \gamma) = Pr\{\boldsymbol{\beta X_m} - \gamma(Y_i - R_m) + \varepsilon_{im} > \boldsymbol{\beta X_n} - \gamma(Y_i - R_n) + \varepsilon_{in}\} \quad (6)$$

$$= Pr\{\varepsilon_{in} - \varepsilon_{im} < \boldsymbol{\beta X_m} + \gamma R_m - \boldsymbol{\beta X_n} - \gamma R_m\} \qquad \forall n \in M; n \neq m$$

which demonstrates that the choice probabilities are determined by indirect utility differences, rather than absolute utilities. The effects of variables that do not vary across attributes (such as income) disappear, and can be excluded. Assuming that the error terms are i.i.d. Type 1 extreme value distributed gives the conditional logit model:

$$P(m: M, \beta, \gamma) = \frac{e^{\beta X_m - \gamma R_m}}{\sum_{n \in M} e^{\beta X_n - \gamma R_n}} \qquad \forall n \in M; n \neq m \quad (7)$$

where parameter estimates are normally obtained through maximum likelihood.

Estimation issues associated with the standard conditional logit model are discussed by Adamowicz and Swait (2011). The model, as described above, does not allow for unobserved heterogeneity (individual characteristics or missing attributes which affect the decision), and many authors attempt to control for such unobservables by estimating Mixed Logit (originally proposed by McFadden and Train (2000)) and Latent-Class models (originally proposed by Swait (1994)). In the Latent-Class models, the marginal utilities are allowed to differ (scaled) according to some unknown discrete class or indicator. In the Mixed Logit, some parameters (chosen by the researcher) are assumed to be random draws from a known distribution (normal or log-normal, for example) and the model is estimated by Simulated Maximum Likelihood (see Train (2009)). This effectively allows the coefficients to vary by individual and, in doing so, permits tastes for the

[51] In choice models it is the utility difference that determines the probability of choice. As the marginal utility of income is constant across choices it cancels out (Adamowicz and Swait, 2011)

particular attribute to vary. However, such methods bundle all possible sources of heterogeneity into a single scaling factor (latent-class) or random effect (mixed logit), without providing an explanation of the underlying differences. Within the mixed logit model, it is also possible to allow the means of the random coefficient to be heterogeneous with observed choice-invariant individual data $\boldsymbol{z_i}$. The model also accounts for the quasi-panel setup of the data (seven choices per respondent in our application). For attribute k, the random coefficient for individual i is:

$$\beta_{ki} = \beta_k + \boldsymbol{\delta_k}'\boldsymbol{z_i} + \sigma_k v_{ki} \tag{8}$$

where $\boldsymbol{\delta_k}$ is a vector of coefficients, v_{ki} is the individual specific heterogeneity (with mean zero and standard deviation one) and σ_k is the standard deviation of the distribution of β_{ki}s around β_k. The model is easily estimated in NLOGIT version 5.

4.2.3 Application

The final choice experiment was created using the survey software package *Qualtrics*. Respondents were invited through the mailing lists (email) of the University *Trinity College, Dublin* (staff and students), where participation was incentivised by way of a raffle (one in ten chance of winning a €50 voucher).[52] Our chosen attributes and levels are based upon the outcome of focus group discussions in which participants were asked to outline their priorities when renting.[53] It should be highlighted that we did not mention energy efficiency at any stage, and both focus group and final survey were presented as general 'rental' surveys. This was carried out to reduce potential response bias, given that

[52] Participation emails (which included a link to the survey) were sent out on April 15th and surveys were then completed over the following 14 days. The survey software collects each respondent's IP address which prevented multiple survey completions (required due to the raffle).

[53] The focus group was conducted in Trinity College Dublin on June 26th 2013 and was attended by administrative college staff, postgraduate students and non-college employees. Participants were asked to discuss and outline 'what they value when looking for a new property' both in groups and individually.

energy and environmental issues are currently topical, emotive and, for many, moral subjects. As a result, the energy features of properties, while featured in the focus group, were low on our group's list of priorities when choosing a property and the BER was not mentioned. Respondents, did, however, mention the heating system characteristics (electricity versus oil, for example), which does demonstrate a degree of energy awareness. In general, the group's priorities could be summarised under 6 attributes: rent, area safety, distance to work, condition, size and energy efficiency (in order of importance).

To reduce the number of opt-outs, we have focused on single-bedroom apartments only, as including all types of rental properties would create an uncontrollable amount of heterogeneity in dwelling type and, more importantly, occupant type, which would increase the complexity of both the experiment and the choice. For example, two-bedroom (and over) properties are often rented by many occupants – this would exclude a number of renters (singles or couples) who do not wish to share and also distort the price vector for those who do (respondent will divide the rent in a manner unknown to us). Both of these effects would bias the coefficients. Furthermore, as rent levels are area dependent, we have focused solely on the Dublin area to ensure that the price vector is realistic for respondents.

The attribute levels were chosen using a variety of sources (all attributes and levels are presented in Figures C.2 through C.8 (Appendix C)). Monthly rent bounds were taken from online searches within Dublin city (single-bedrooms only) on daft.ie. For area safety, official Dublin crime statistics (available from the Irish Central Statistics Office (www.cso.ie)) were used to create an 'average' safety area which was scaled up and down for high and low crime rates. To improve the realism of the choice task, we incorporated the size attribute (small, medium and large) into three apartment diagrams. Distance to work and condition were chosen based on focus group responses and ranges from 10 to 60 minutes.

For energy efficiency, we applied both the current rating policy (the BER) and also converted this kWh figure into a monetary equivalent. Each participant is shown either the BER as an alphabetical number (A through F) or an estimated 'Typical Energy Bill' in monetary terms (€ per month) (the format that each participant is presented was chosen at random by the survey software). This second efficiency measure is included to explore if the willingness-to-pay for energy efficiency improvements differs when communicated in quantitative (kWh) or monetary terms. For example, Chapter Three outlines a number of previous studies which show that monetary units can have a positive effect on the demand for energy efficiency (see for example, Newell and Siikamäki (2013), and Codagnone et al. (2013)).

As the full 15 subcategories in the BER (see Figure C.1) is too many for the experimental design software (maximum of six), we opted to include only the main alphabetical grouping without subcategories (A through F). The kWh/m^2/annum associated with each category was then used to create a 'Typical Energy Bill' (TEB). This calculation follows the advice of the national energy authority (SEAI) and is based on the cost of lighting, fans and pumps (C_{LFP}) plus the cost of space and water heating (C_{SW}):

$$TEB = [C_{LFP} + C_{SW}]/6$$

$$TEB = \left\{[P_{ELY} * Size * F_E] + [P_G * Size * \frac{kWh-(L*F_E)}{F_{GAS}}]\right\}/6 \quad (9)$$

where P_{ELY} (€0.23) and P_{GAS} (€0.08) are electricity and gas prices respectively (used for space and water heating), F_E (2.45) and F_G (1.1) are primary energy conversion factors for fossil fuels and electricity, and L is the energy demand for lighting, fans and pumps (assumed to be 9 kWh/m^2/annum). The denominator converts the annual cost into a typical bimonthly bill. To illustrate, a 40m^2 apartment with a BER rating of 380 kWh/m^2/annum (an 'F' rating) will have a TEB of €192.77. These energy prices are at the higher end of

current retail prices and this energy cost forecast (and WTP) may be considered as an upper bound.

Our experimental designs were carried out using *NGENE* (version 1.1.1). We choose a fractional 'shift' or 'D-optimal' design (following Street et al. (2005)) for 28 rows and four blocks (four choice sets each with seven choice situations). This method maximises attribute level differences while maintaining design orthogonally (attribute level balance and zero correlation between attributes). Table C.1 (Appendix C) presents the full experimental design.[54] Furthermore, we have allowed for an opt-out alternative to improve the credibility of the survey – in the real world, prospective renters will never *have* to choose between two apartments and will just continue searching until an optimal property is found. A status quo option, while ideal, is not possible, as many renters are both unaware of their current apartment size and their BER rating (highlighted in our focus group).

Hypothetical bias is a concern in any stated preference analysis. However, relative to wider literature, this choice experiment is less abstract – we are not valuing a new product, service or public good, and the attributes and associated levels are, we must assume, generally well understood by the public (particularly so given our targeted sample of renters). Also, for the renter, the choice of a new property has a potentially large financial implication and the majority of respondents will have already faced these attribute trade-offs in the past. This, we expect, will make the decision less hypothetical/complex and more credible for respondents, hopefully leading to less bias in response. As the choice and attributes are already familiar we expect fewer 'learning effects' associated with increased market experience (List, 2003) and, as a consequence, the utility function should stay reasonably stable throughout the experiment (Carlsson, 2011). Furthermore, as the

[54] The original design included eight choices per respondent. However, this design resulted in three dominant alternatives and therefore the final design was reduced to seven choices per respondent (one choice task randomly deleted).

experiment has been presented as a 'rental' survey and the respondent is choosing a private good/service with no non-use value and few public good elements, there is perhaps less motive to choose strategically. Finally, a standard 'cheap talk' section (Cummings and Taylor, 1999) is included to motivate respondents into providing an unbiased answer by highlighting the prevalence of hypothetical bias in comparable research. Also, a list of pre-survey 'warm-up' questions are included to frame the choice set and to encourage the respondent to think about the value of attributes prior to the choice task. An example of a choice task is provided in Figure C.9 (Appendix C).

4.3 Results

The analysis focuses only on respondents who have either been a tenant at some stage in the previous four years or are currently looking for a rental property (86% of completed surveys). Of these responses (1,748 individuals), 865 completed Sample A (energy efficiency presented as the 'BER') and 883 completed Sample B (energy efficiency presented as a 'Typical Energy Bill'). Descriptive statistics for the sample are presented in Table C.2 (Appendix C). The college sample consists mainly of students (68% undergraduate or postgraduate) followed by staff (28% academic or administrative). Average monthly net income (€1,336) and age (27 years) are therefore below national rental averages (€3,158 and 35 years) while education levels are higher (62% of the sample have a third level degree or above, compared to 32% in the population).[55]

There are a number of qualitative responses worth highlighting prior to the formal econometric analysis. For example, Tables 4.2 and 4.3 present respondent's self-reported

[55] Author's calculations based on the Irish Household Budget Survey 2004-2005 received from The Irish Social Science Data Archive at www.ucd.ie/issda/issda.

attribute importance (asked immediately after the DCE) for samples A and B respectively. In both, Rent, as expected, is ranked highest (over 95% responded with either a '4' or '5' in both samples) and is followed by Distance to Work, Area Safety, Condition and Size. The BER, while still important to 44% of respondents in Sample A, is ranked lowest and shows the highest levels of indifference ('3') and unimportance ('1' or '2'). The 'Typical Energy Bill' is, however, considered more favourably than the BER, with 72% of respondents considering this attribute as important.

Table 4.2: Self-Reported Attribute Importance (percentages) – Sample A

	Rent	Size	BER	Area Safety	Condition	Distance to Work
1. Not Important at All	0.35	9.56	9.66	2.09	2.32	0.82
2. Slightly Unimportant	1.27	19.7	22.12	8.49	8.25	1.86
3. Neither Important or Unimportant	2.09	16.67	24.33	12.33	21.6	4.43
4. Slightly Important	16.11	41.61	35.62	32.56	49.01	30.42
5. Very Important	80.19	12.47	8.27	44.53	18.82	62.47

Table 4.3: Self-Reported Attribute Importance (percentages) – Sample B

	Rent	Size	'Typical Energy Bill'	Area Safety	Condition	Distance to Work
1. Not Important at All	0.46	9.02	1.82	2.17	2.85	0.46
2. Slightly Unimportant	0.34	25.57	10.48	11.43	14.01	2.74
3. Neither Important or Unimportant	1.37	20.55	15.26	13.83	19.48	5.71
4. Slightly Important	17.43	36.07	51.48	31.66	49.89	31.85
5. Very Important	80.41	8.79	20.96	40.91	13.78	59.25

Table 4.4 presents results from the conditional logit model for apartment choice in samples A and B plus both samples combined (Sample C). Since the choice experiment is unlabelled, specifying alternative specific constants would not make sense (there should be no underlying utility difference between alternatives). We do, however, include a constant for the 'neither' option, which recognises that there is utility attached to not choosing (this is the only variable in the 'neither' utility function). To interpret these results, marginal

willingness-to-pay (WTP) estimates are presented in Table 4.5.[56] While all attributes are statistically significant, WTP confidence intervals for samples A and B demonstrate that differences between samples are, in general, not significant (although in Sample B, the WTP for high safety areas is higher and the WTP for size is no longer significant). In all samples, safety and location are strongly valued. While low crime areas are valued higher than average crimes areas (WTP increases by €74 in Sample C), there is a very strong disutility associated with low crime areas – on average, respondents are willing to pay €353 more rent per month to live in an average safety location compared to a high crime area. This high WTP may, however, be driven by the demographics of the sample, with 87% describing their current area as 'safe'. For distance to work/college (time), renters will pay about €11 more for every minute reduction in travel time. This latter result is, however, likely skewed upwards by the strong disutility associated with the upper value of this attribute (60 minutes).[57] For condition, similar results are observed, with the WTP estimates relatively larger for low (10 years old) to medium (5 years old) improvements (€63 more per month) relative to medium to high (brand new) improvements (€38).

In all models in Table 4.4, the efficiency attribute (continuous variable from 1 to 6) is interacted with size (30, 40 or 50 m^2) to allow for higher efficiency valuations for larger apartments. In the combined sample, the sample indicator (dummy variable 'B') interaction controls for potential efficiency differences between samples A and B. The results show that the WTP for energy efficiency significantly increases with size. In Sample A, the WTP for efficiency in small apartments (30 m^2) is small and insignificant,

[56] WTP standard errors are calculated using the 'Wald' command within NLOGIT (version 5)

[57] For example, if the model is estimated with distance dummies (not shown), the WTP for high to medium improvements (60 to 30 minutes) is €409 euro (or €13.6 per minute) while the WTP for medium to low improvements (30 to 10 minutes) is €158 euro (or €7.9 per minute). As 86% of our sample currently live within 40 minutes (pre-survey question), the lower WTP estimate is likely more appropriate.

but increases to €21 for medium (40 m^2) and €35 for large (50 m^2) apartments.[58] However, as highlighted above, there is no significant difference in the mean WTP between these samples, whether comparing WTP estimates between samples (A verses B) or modelled simultaneously and including a sample interaction. While the WTP for efficiency in large apartments appears to be higher in Sample B (€44 compared to €33 in the combined sample), the confidence intervals are heavily overlapping.[59] Overall then, for an average sized apartment (40 m^2), the marginal WTP for efficiency improvements, whether in BER units (a 'D' to a 'C', for example) or in equivalent monetary terms, is around €20.

Table 4.4: Conditional Logit Model Results

	Sample A: 'BER'		Sample B: 'Typical Energy Bill'		Sample C: Combined	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Condition Low [D]	-0.178***	0.061	-0.255***	0.059	-0.216***	0.042
Condition Ave. [D]	---------- reference group ----------					
Condition High [D]	0.128**	0.057	0.129**	0.055	0.129***	0.039
Safety Low [D]	-1.212***	0.059	-1.197***	0.058	-1.204***	0.041
Safety Ave. [D]	---------- reference group ----------					
Safety High [D]	0.183***	0.053	0.319***	0.052	0.252***	0.037
Distance	-0.038***	0.001	-0.038***	0.001	-0.038***	0.001
Rent	-0.003***	0.000	-0.003***	0.001	-0.003***	0.000
Size	-0.002	0.008	-0.024***	0.007	0.000	0.007
Eff. (Efficiency)	-0.120	0.082	-0.251***	0.080	-0.097	0.073
B [D] (Sample B)	-	-	-	-	1.225***	0.342
Size*Eff.	0.005**	0.002	0.008***	0.002	0.004**	0.002
Size*B	-	-	-	-	-0.027***	0.008
Eff.*B	-	-	-	-	-0.173**	0.088
Size*Eff.*B	-	-	-	-	0.004*	0.002
Constant ('neither')	-4.768***	0.346	-5.943	0.339	-4.740***	0.297
N	6055		6181		12236	
Individuals	865		883		1748	
Log Likelihood	-5425.73		-5503.54		-10932.04	

Note: [D] indicates dummy variable, *** significance at 1%, ** at 5% and * at 10%

[58] WTP in the presence of interactions is estimated by differentiating the utility function with respect to the variable of interest. For example, for utility function $V_i = \beta_C C_i + \beta_E E_i + \beta_S S_i + \beta_{ES} E_i S_i + e_i$ the WTP then equals $WTP_E = -(dV_i/dE_i)/\beta_C = -(\beta_E + \beta_{ES} S_i)/\beta_C$, where C_i is the monetary attribute (cost or income).

[59] 95% confidence intervals of [19.77 | 47.08] and [30.73 | 58.24] in samples A and B respectively

Table 4.5: Marginal Willingness-to-pay (WTP) Estimates

	Sample A: 'BER'		Sample B: 'Typical Energy Bill'		Sample C: Combined	
	WTP	Std. Err.	WTP	Std. Err.	WTP	Std. Err.
Condition Low (D)	-53.320***	18.322	-73.630***	17.263	-63.658***	12.558
Condition High (D)	38.449**	17.009	37.173**	15.728	38.087***	11.55
Safety Low (D)	-362.957***	19.563	-344.870***	18.069	-353.498***	13.275
Safety High (D)	54.861***	15.502	91.874***	14.491	74.054***	10.581
Distance	-11.556***	0.437	-11.179***	0.404	-11.354***	0.296
Size @ Eff.=3.5	4.444***	0.729	0.867	0.683	2.617***	0.497
Eff. @ Size=30	6.965	7.328	-3.361	6.837	-	-
Eff. @ Size=40	21.233***	4.356	19.580***	4.144	-	-
Eff. @ Size=50	35.500***	7.771	42.521***	7.535	-	-
Eff. @ Size=30 & B=0	-	-	-	-	8.573	6.536
Eff. @ Size=40 & B=0	-	-	-	-	20.998***	4.133
Eff. @ Size=50 & B=0	-	-	-	-	33.423***	6.967
Eff. @ Size=30 & B=1	-	-	-	-	-5.107	6.373
Eff. @ Size=40 & B=1	-	-	-	-	19.688***	4.067
Eff. @ Size=50 & B=1	-	-	-	-	44.484***	7.019

Higher order socio-demographic interactions are cumbersome within the above specification. However, the mixed logit (or random parameters) model can accommodate increased levels of heterogeneity (choice-invariant). Within this more flexible framework, we define the efficiency coefficient as a normally distributed random parameter, and allow the mean to be a function of age and income, and, for consistency with Table 4 above, size and the sample indicator.

Results for the mixed logit model are presented in Table 4.6. The WTP estimates are similar to the conditional logit (sample C) and, with the exception of 'Safety High', are not statistically different to Table 4.5. While the mean WTP for efficiency is also statistically indistinguishable, there are a number of significant heterogeneity variables. For example, mean efficiency is negatively influenced by age, which implies that older respondents place a lower value in energy efficiency. A ten year increase in age of respondent, for example, reduces the WTP for efficiency by about €15. Consistent with Table 4.4, the sample indicator is insignificant and the size variable is positive and significant, although

the magnitude of the size effect is smaller than Table 4.5 and suggests that a 10 m^2 increase in size reduces the WTP by about €5. Finally, income does not influence the WTP for energy efficiency, but this result should be interpreted in light of the college sample with very low income levels.

Table 4.6: Mixed Logit Model Results

	Coef.	Std. Err.	WTP	Std. Err.
Non-Random Parameters:				
Condition Low [D]	-0.250***	0.041	-54.334***	8.995
Condition High [D]	0.150***	0.039	32.602***	8.435
Safety Low [D]	-1.531***	0.048	-333.257***	10.375
Safety High [D]	0.550***	0.040	119.787***	8.041
Distance	-0.049***	0.001	-10.686***	0.228
Rent	-0.004***	0.000	-	-
Constant ('neither')	-4.662***	0.122	-	-
Random Parameters:				
Eff. (Efficiency)	0 .189***	0.060	19.286***	3.546
Heterogeneity Parameters:				
B [D] (Sample B)	0.030	0.024	6.468	5.212
Size	0 .002***	0.001	0 .495***	0.160
Age	-0.007***	0.002	-1.510***	0.452
Income	0.000	0.000	-0.003	0.003
N	12236			
Individuals	1747			
Log Likelihood	-10183.40			
Halton Draws	50			

4.4 Discussion

There are a number of issues which are preventing the Irish energy efficiency certification system from reaching its potential. For example, there is existing evidence that most landlords have not yet completed a BER certification and are therefore not currently advertising efficiency information when seeking new tenants, despite the possibility of prosecution and fines. We have also presented previous evidence that the advertised BER

ratings in Ireland are skewed upwards by deliberate non-disclosure and/or misrepresentation, leading to an over/under-representation of high/low efficiency properties. These real-world observations are supported by our own survey findings. Of the 94% of respondents who rented a property in the last four years (1,638 individuals), just 12% were shown the BER information for the property. However, as renters must ask for this information, this low percentage of disclosures may also be driven by renter unawareness of the BER system or renter indifference to energy efficiency. The latter may be supported by the high percentage of renters in our survey who cannot recall their specific BER rating when it was provided (58%). Our survey also highlights another potential demand issue which may reduce understanding of the current rating system – it is evident that renters show little understanding of property size, and most (53%) do not know the size of their current accommodation. Since the expected energy consumption of an apartment is a function of size within the BER system (kWh/m^2), it is possible that this lack of understanding may limit renter utilisation.

The hypothetical rental situation presented in this paper differs to the real-world market in a number of ways. First, we change supply conditions by providing a BER certification for every property, second, tenants do not have to ask for this information (it is displayed for each apartment), and, third, we influence the choice environment by providing every tenant with descriptive information of the BER (identical to the regulator's), which will increase tenant understanding of the rating system. We have therefore created a rental market with complete and accurate energy efficiency disclosure by landlords and improved awareness by prospective tenants. This hypothetical situation, while currently far from the real-world, is the current policy goal and will be achieved with increased enforcement.

Our results show that renters do value energy efficiency within these hypothetical conditions. Overall, the WTP for BER improvements, while lower than that for all other

property attributes is, positive and significant, and around €20 for each full letter BER increase (a 'C' to 'B', for example) or, equivalently, a 1.8% rental premium given the average rent of €1100 per month in the experiment. Converting this same information into a monetary estimate (the 'Typical Energy Bill') does not significantly change the WTP, despite respondents viewing this attribute as more 'important' in post-experiment survey questions. Our estimate is very similar to the average expected monthly energy savings associated with BER improvements. For example, for a $40m^2$ apartment, moving from a 'D' to 'C' efficiency rating will save around €19 per month (based on Equation 9). Assuming no rebound effect, our estimates therefore suggest that renters are rationally minimising costs in a fully informed rental market (the notion of 'rational', however, is purely financial, and excludes any utility associated with being more environmentally friendly). Our WTP estimates are very similar to previous revealed preference analysis in Ireland. The results of Hyland et al. (2013), for example, show that each subcategory BER increase (see Figure C.1) raises rents by 0.5%. Given the average rent of €1005 in their sample, the associated rent increases for a full categorical increase (C2 to B2, for example) is around €15.[60] Furthermore, they show that a 'D' to 'B' BER improvement increases rents by about 4.2% (using BER dummy variables) which is identical to the current analysis (4.1%).[61]

Finally, over longer timeframes, will landlords invest in energy efficiency? While we have not formally forecasted supply effects, the above provides landlords with a straightforward cost-benefit decision. Although the cost of retrofits and technology upgrades are highly heterogeneous, information on sales premiums associated with BER improvements is available from Hyland et al. (2013). We can therefore hypothesise the purchasing decisions

[60] For comparison with the present study, we use [€1005*(1.005)^3] – €1005 = €15.15 for a full category increase (C2 to a B2, for example). This full 15 group subcategory scale is, however, highly nonlinear with respect to energy consumption. For example, the reduction in energy associated with an 'F' to 'E2' and a 'B1' to 'A3' improvement is 60kWh and 25kWh respectively.

[61] Running our models with dummy variables for BER rather than continuous (not shown) gives a 'D' to 'B' WTP estimate of €45. Given the average rent of €1100, this represents a 4.1% increase.

of the average 'buy-to-let' investor. Hyland et al. (2013), for example, show that each BER subcategory improvement is associated with a 1.3% increase in sales price. Given the average price of €146,000 for a single bedroom apartment in Dublin city centre (DAFT, 2014), a full category increase (C2 to B2, for example) will cost an extra €5768.[62] The annual rental premium attached to equivalent efficiency improvements is, however, currently €240 (€20 per month, as described above). Whether or not a landlord will invest in the higher rated property will depend on the assumed discount and rent inflation rates. For example, if we assume a relatively low discount rate of 4.5% (approximate current mortgage interest rate) and that rents will increase by 2% per annum, it will take around 37 years to recover the investment.[63] This is likely longer than the life of most energy-saving technologies (a new boiler may last 25 years, for example). For context, the regression controls included in the analysis of Hyland et al. (2013) provide an interesting comparison. For example, while our results demonstrate that the WTP for a large 'D' to 'B' efficiency improvement is about 4%, their analysis shows that this is about the same as that premium associated with installing a dishwasher or cable TV, two investments with *considerably* lower capital costs. The costs of retrofits (compared to buying) are, however, unknown and may portray a more favourable investment situation.

4.5 Conclusion

This paper estimates the willingness-to-pay (WTP) for energy efficiency improvements in the rental market. Within a stated preference choice experiment, we employ a recent informational policy instrument – the *Building Energy Rating* (BER) – which provides an independent, state-monitored energy efficiency score (kWh/m^2/annum) for prospective

[62] [€146,000 * (1.013) ^ 3] – €146,000

[63] $NPV = \sum_1^T \frac{€240*(1+.02)^T}{(1+0.045)^T} - €5768.$

tenants. The BER removes the landlord-tenant asymmetric information problem related to energy efficiency. Our choice experiment includes a number of property attributes highlighted in our focus groups; attributes which are highly valued but not readily available in revealed preference data. We also convert the BER into a 'Typical Energy Bill' to explore if WTP increases when energy efficiency is communicated in monetary units rather than physical. Our analysis differs to the current market in that energy efficiency information is provided for every property and, furthermore, every renter is provided with a background of the rating system prior to choosing.

In this fully informed hypothetical situation, our results show that energy efficiency, although among the least important characteristics when choosing a property, is significantly valued by renters. However, the increase in WTP is small (1.8% of mean rent for a full BER letter increase) which is likely to be too low to promote significant efficiency investment by landlords. Furthermore, our results show no significant difference in WTP when monetary units are employed, despite the fact that respondents are not aware of property size. To conclude, these results suggest that the main determinant of the renter-owner efficiency divide in Ireland is low energy efficiency investment returns for landlords, with asymmetric information playing a more minor role. While the latter undoubtedly has some effect, these results show that correcting the problem is unlikely to create a market which will promote efficiency investment. Governments wishing to reduce the energy consumption of rented properties could, of course, impose minimum efficiency standards. However, this would undoubtedly reduce supply and raise rents, which could put renters at an even higher financial disadvantage. Results also show that age and size significantly affect the WTP for energy efficiency. It is therefore possible that the WTP will increase in the future as older renters leave the market and buy their own properties (assuming that the current younger generation remain energy conscious). Furthermore, given the significant effects of size, the current analysis may undervalue efficiency

improvements due to the focus on single-bedroomed apartments. However, given that Irish renters show a very poor understanding of property sizes, this significant size effect is likely to be survey-dependent (apartment size and efficiency were presented in conjunction, which is unlikely the case in Ireland). Given that our results show clear complementary effects in providing this information simultaneously, we recommend that the current efficiency labelling and advertising legislation be amended as such.

Chapter 5

Conclusion

5.1 Main Findings, Policy Recommendations and Future Research

This thesis has explored the role of energy information in various formats and markets, and discussed the likely effects of market failures relating to imperfect or asymmetric information. This chapter describes my overall conclusions, potential areas for further research and, where applicable, recommendations for policymakers. Section 5.2 returns to the trends in global greenhouse gas (GHG) emissions first presented in Chapter 1, while Section 5.3 discusses the potential role that household information will play in meeting overall reduction targets.

5.1.1 Paper 1 – The Role of Knowledge Improvements in Electricity Markets

Previous research has shown that improved consumption feedback significantly lowers household electricity demand, both in Ireland and internationally. Paper 1 attempted to uncover the cause of such reductions by exploring the role of knowledge improvements observed during a smart metering trial. The results show that households with improvements did not reduce any more than households without. This finding brings into question a 'imperfect information' rationale for feedback intervention. There are, however, a number of caveats which frame this result. First, this was a short-term study based over

one year, and it is possible that improvements in knowledge will have a demand-reducing effect through more efficient technology adoption over longer time periods. It is therefore recommended that future research explores the medium/long-term investment decisions following informational interventions. Second, and most importantly, the proxies employed for household knowledge change are self-reported and therefore potentially biased. The proportion of households who showed knowledge deteriorations (about a fifth) highlights the potential for error. Future surveys could reduce this bias by formally testing this knowledge by directly asking households about which appliance and behaviours consume the most.

The paper provides limited policy input. The feedback given during the Irish trial did produce the intended behavioural effects – treated households significantly reduced their electricity demand. The contribution of this paper is that it highlights that these reductions are driven by factors other than knowledge improvements. This and previous research may, however, be used to inform the specific informational content and frequency of future electricity feedback. For example, increased feedback may decrease the costs of changing household energy-consuming habits and routines – if we assume that households already want to (and know how to) reduce their demand, but perhaps lack the self-discipline to change long-term patterns of behaviour, then it is possible that feedback decreases electricity consumption because it merely increases the number of reminders. The insignificant effects of the bi-monthly user statement versus the monthly statement (same information but more regular) may support this hypothesis. Similarly, if we assume that households are concerned about their environmental impact and there is an individual disutility associated with energy consumption, it is possible that feedback increases the guilt or moral cost of consuming.

5.1.2 Paper 2 – The impact of lifetime energy cost labels on appliance purchases

Buying the most energy efficient products, from electric cars to solar panels to low-consumption appliances, generally requires an increased initial purchase price relative to the status quo technology (holding all other product attributes fixed), which is then compensated with decreased future energy costs. The energy efficiency gap describes the aggregate failure of households to invest in more energy efficiency technologies, despite the fact that they often represent the cost-minimising alternative over the life of the product. Paper 2 outlined the number of reasons why this may be the case, including imperfect information, uncertainty, loss aversion and status-quo bias. The paper, however, only tests one potential behavioural failure – that buyers are either inattentive or unable to calculate the total costs of their energy-consuming products. This is tested by adding a 'lifetime' consumption cost label to the entire tumble dryer lineup in four stores of an Irish retailer. While the descriptive results show an improvement in mean efficiency in treatment stores, the regression analysis demonstrates that this increased demand for energy efficiency is not statistically significant.

However, it is possible that this result is applicable to one technology type (tumble dryers) and one geographic location (the Greater Dublin Area). Future research could therefore conduct similar trials on other energy consumables (other appliances, cars or building technologies), within other geographic areas (EU countries with higher/lower income and energy prices, for example) and with different cost forecast durations. For the latter, previous research has shown that duration matters, and that shorter cost forecasts have no effect. It is therefore possible that the results of this paper are at the lower end. Furthermore, the impact of lifetime labels could be increased by providing heterogeneous consumers with tailored energy cost information dependent on their specific energy behaviours and circumstances (use intensity, energy prices and expectations), perhaps through applications on smart phones, interactive displays in retail outlets or through adaptive websites. There is therefore clearly much room for further research.

5.1.3 Paper 3 – Low energy efficiency in rental properties and the effects of the BER

Rental properties have significantly lower levels of energy efficiency than owner-occupied. Asymmetric information in relation to a property's energy attributes helps explain this owner-renter efficiency divide as it describes a market with uncertain quality for buyers, or an equivalent rental market 'lemons' problem: as renters cannot differentiate between high and low efficiency (without cost) they will assume an average, and landlords, knowing that energy efficiency is not rewarded through higher rents, have no incentive to invest. Independent energy efficiency ratings provide a clear solution to the information asymmetry. However, both the problem and the solution rest upon one important assumption – that the willingness-to-pay (WTP) for energy efficiency in a perfectly informed rental market covers the cost of capital. In paper 3, this market environment was artificially created by way of a choice experiment. Respondents were first presented with a description of the rating system (the Irish Building Energy Rating (BER)) and then asked to choose from multi-attribute apartments which included this information. BER levels were also converted into a monetary equivalent to explore whether this format increased WTP for energy efficiency.

Results show that increases in energy efficiency are valued by renters, but significantly less than improvements in other property attributes such as location, area safety, size and condition (for attribute level changes, as defined in the survey). The BER is also ranked lowest by respondents in follow-up survey questions. Furthermore, the monetary efficiency attribute did not significantly change renter efficiency valuation. Overall, the marginal WTP for BER improvements is around €20, but increasing with property size. For landlords, this increase is likely to be too low to promote energy efficiency investment (for the given experiment – one-bedroomed apartments). Therefore, while asymmetric information likely plays a role in the owner-renter divide, low WTP will have prevented

and will continue to prevent investment in the future. Renter efficiency valuation, however, appears to be rational (cost-minimising), with increases in rents similar to expected energy savings. Therefore, provided renters are actually rational cost-minimisers, market forces under perfect information will only lead to energy investment with large energy price increases.

These research questions were explored using a large sample of renters (1,748 individuals) at Trinity College, Dublin. Future work should therefore explore if similar results are found for the renting population at large. Furthermore, increased numbers of property types, while increasing the complexity of the design exponentially, could highlight differences in efficiency valuation, particularly in relation to property size. The policy recommendations are, however, limited - the BER, although unlikely to bring efficiency improvements for small properties, is 'working', and alternative efficiency formats (the 'Typical Energy Bill') are unlikely to bring higher efficiency valuations. However, the choice experiment did differ to the Irish market in one aspect – properties were described using size (m^2) and this attribute and unit of measurement is often omitted from property advertisements. Given that the BER rating system uses m^2 in its rating ($kWh/m^2/annum$), it is suggested that BER certificates and advertisements should also.

5.2 International Greenhouse Gas Trends

Chapter 1 presented the long-term trends in CO_2, the recent changes to the world's climate and the predicted damaging effects of rising temperatures due to GHG emissions over the next century. The EU has made considerable progress in GHG abatement since 1990, and data from the European Environment Agency (EEA) show considerable reductions of 19%

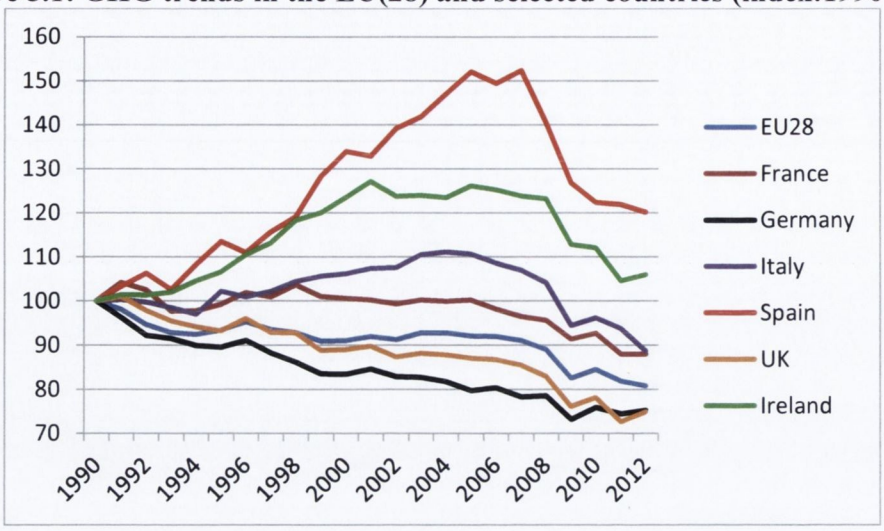
for the EU(28) (Figure 5.2).[64] Furthermore, the EU(15) Kyoto target (average GHG reduction of 8% between 2008-2012 compared to base years) has been met, with average reductions of 12% observed for this period and group of countries (European Environment Agency, 2014).[65] Declines have, however, been partly driven by decreased economic activity since 2008. For example, the GHG reductions observed in the five years since 2008 (10%) are about the same as those observed in the previous 17 years (1990 and 2007). Some EU countries have made particularly large reductions, most notably Germany and the UK. For sectors, Table 5.1 presents changes (between 1990 and 2012) for the EU's five highest emitters, which together account for 78% of total emissions (in 2012).[66] It is evident that the GHG trends in Figure 5.1 are driven by large reductions in residential, agriculture, manufacturing and electricity/heat sectors. However, emissions from transport, the second highest GHG emitter in the EU, have increased by 14%. This is partly driven by large increases in aviation (93% increase) and maritime (32%), which together account for about 30% of transport (not shown). Ireland's GHG emissions, while above 1990 levels, show large improvements since 2005. This overall increase is, however, within Ireland's specific GHG target (13% *above* 1990 levels) for the 2008-2012 period. For Irish sectors, reductions are observed for residential (17%) and agricultural (8%), while the remaining all show increases (particularly transport, which increased by 113% since 1990).

[64] GHGs include methane, nitrogen dioxide, hydrofluorocarbons, perfluorocarbons and sulphur hexafluorides.

[65] Base years differed by country but most used 1990. The methodology does not include emissions/removals from land use change (increased urbanisation, for example) and forestry (removal or planting of forests, for example) or emissions from international aviation and international maritime.

[66] 'Residential' GHG emissions are related to gas, liquid and solid fuels used for household heating, 'Transport' are related to diesel, petrol and oils used on roads, railways and navigation (includes residential use) and 'Public Electricity and Heat' refers to gas, liquid, solid and 'other' fuels used in generation.

Figure 5.1: GHG trends in the EU(28) and selected countries (index:1990=100)



Note: Data downloaded from the European Environment Agency (www.eea.europa.eu)

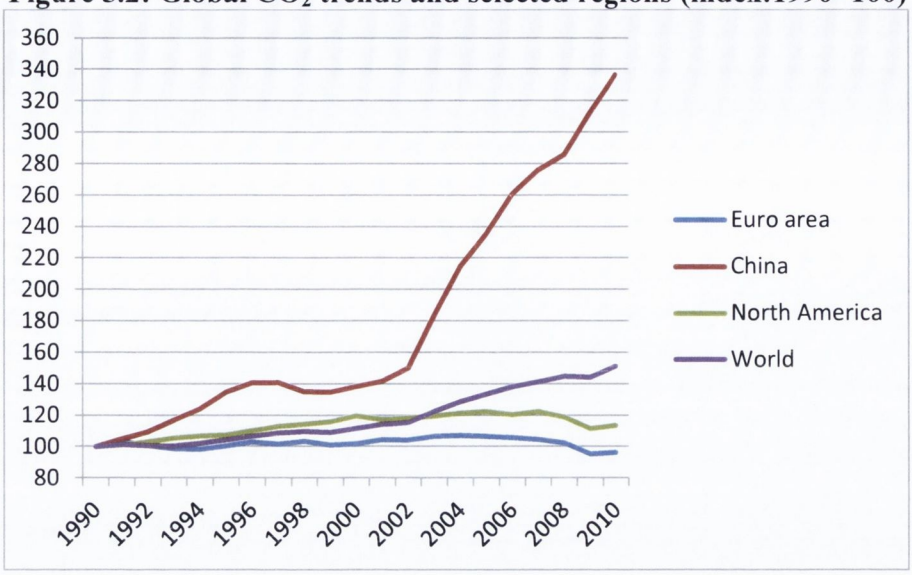
Table 5.1: GHG emissions in the EU(28) and Ireland

	Share of total emissions		% change 1990-2012	
	EU(28)	Ireland	EU(28)	Ireland
Residential	9.36%	10.58%	-18.73%	-16.91%
Agriculture	10.32%	30.70%	-23.99%	-8.49%
Manufacturing Industries and Construction	11.73%	7.31%	-38.05%	7.94%
Transport	19.65%	18.62%	14.12%	112.84%
Public Electricity and Heat Production	26.96%	21.14%	-14.72%	12.96%

Note: Data downloaded from the European Environment Agency (www.eea.europa.eu)

Global emissions, however, describe a very different trend. Figure 5.1 presents global CO_2 (the main GHG contributing to climate change) trends between 1990 and 2010, and also for North America, the EU and China, which together account for half of global emissions. In this 20 year period, global emissions increased by about 50%, and, with exception to the recession in the late 2000s, have generally shown steady annual increases since 1990 (average 2.5% per annum). While some countries have shown declines – the EU has decreased by 4% since 1990 and North America by 10% since 2004) – other regions have shown large increases, most notably in China, whose CO_2 emissions have grown by 240% since 1990.

Figure 5.2: Global CO_2 trends and selected regions (index:1990=100)



Note: Data downloaded from the World Bank (data.worldbank.org). CO_2 stemming from the burning of fossil fuels (solid, liquid and gas fuels and gas flaring) and the manufacture of cement.

5.3 GHG Abatement and the Role of Households and Information

In order to limit the most damaging effects of climate change, large reductions in worldwide GHG emissions are needed. This will not be achieved without considerable changes to technologies, behaviours, developments and the movements of goods and people. The most optimistic climate change scenario of the International Panel on Climate Change suggests that global GHG emissions in 2050 will need to be 40-70% lower than today's and close to zero by 2100 to keep CO_2 concentrations at 450 ppm and global temperatures rises to less than 2 degrees Celsius. Given the consistent and increasing increases in global GHG emissions over the last 50 years, future reductions will be extremely challenging. Furthermore, at present, the policy goals of increasing living standards and reducing GHG emissions are not compatible, given the clear link between global growth, energy demand and GHG emissions (globally). The EU and other more developed countries have, however, shown that decoupling emissions from economic growth is possible and that large reductions are achievable. Whether similar policies can be

applied to less developed countries, where the stocks of energy-consuming products are only now being accumulated (rather than improved), remains to be seen.

Chapter 1 outlined a number of policies used in the EU to date. Policymakers can reduce GHG emissions by shifting supply and/or demand in energy markets (electricity, fuels and technologies). They must also decide whether to adjust market conditions (but allow market forces to function freely) or to impose quantity restrictions on emissions, behaviours and/or technology types. The EU's supply policies currently employ a mixture of both. The current carbon trading system, for example, puts an upper bound on the number of pollution permits each year but then allows market participants to trade freely. Other quantitative-type regulations include product efficiency limits for manufacturers and minimum energy standards for new buildings. Demand shifting policies in the EU are comprised of taxation changes (carbon taxes on fuels), subsidies (for efficient technology investment) and energy-related information. There are currently no demand restrictions in place for households, and unlike the business sector, there are no competitive forces to penalise deviations from cost minimisation. Informational policy, however, attempts to direct households towards technologies and behaviours which will help them to reduce their carbon footprint and energy costs.

This thesis has explored the effect of a number of specific informational policies to shift demand, either by changing consumption behaviours or investment decisions. Households play a large role in global GHG emissions. For example, in Ireland, the residential sector accounts for 27% of primary energy demand (gas, liquid and solid fuels and electricity) and half of the transport sector (Ireland's highest energy user – 32% of primary energy demand). While informational policies will play a role in reducing household demand, the magnitude of the effects observed in this thesis suggest that, currently, this role will be a minor one (given the scale of global GHG reduction targets). For example, smart metering

feedback is shown to reduce annual demand by 2.5%. This feedback was, however, combined with very large peak tariff increases, and, therefore, a pure informational effect is likely to be considerably smaller. Paper 2 discussed the many reasons as to why households may not invest in the most energy efficient technologies and explored the role of inattention to long-term energy costs. It is shown that 'lifetime' energy cost information has, again, a small demand reducing effect – the average annual consumption of tumble dryers sold in treatment stores reduced by about 3% (however, this effect is not statistically significant). Finally, property energy efficiency information, while reducing the asymmetric information problem, is unlikely to reduce energy demand in rental markets as the resulting rent increases are too small to reward investment.

The results of these experiments are, however, specific to prevailing market conditions, and in particular, to current energy prices and consumer tastes and behaviours. Furthermore, the results are based on Irish data and their applicability to an international context is unknown. In the future, however, informational policies may support and complement other energy-reducing drivers. For example, it is likely that labelling and feedback will be necessary and important for increasing the demand-reducing effects of future energy price increases, whether these be driven by policy (ETS or direct carbon taxes) or by fundamental market forces (shortages in supply). Furthermore, as the effects of climate change become more visible in the future, household motivation to reduce may also increase. Informational policies, such as those explored in this dissertation, may well be complementary to these other drivers of household demand reductions.

Appendix A – Paper 1 Supplementary Information

Table A.1: Descriptive Statistics of Interaction Variables

Label	Description	Mean
TENURE1 [D]	rents	0.063
TENURE2 [D]	owns outright	0.555
TENURE3 [D]	owns mortgage	0.383
HOUSE1 [D]	apartment	0.016
HOUSE2 [D]	attached	0.441
HOUSE3 [D]	detached	0.543
AGE1 [D]	18-35 years	0.094
AGE2 [D]	36-55 years	0.442
AGE3 [D]	55+ years	0.457
AGER [D]	refused to respond to age	0.007
CHILD [D]	presence of young children	0.269
FEMALE [D]	respondent female	0.497
EDU1 [D]	primary	0.128
EDU2 [D]	secondary	0.455
EDU3 [D]	third-level	0.364
EDUR [D]	refused to respond to education	0.053

Note: 'D' indicates dummy variable

Table A.2: Descriptive Statistics for Aggregate Electricity Demand (kWh) 2009/2010

	Total		Peak		Off-Peak	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
2009						
Control	2039.52	1010.73	283.06	153.49	1756.46	873.41
BI-MST	2102.88	1013.19	292.62	150.53	1810.26	879.16
MST	2132.71	1068.41	295.43	157.27	1837.28	927.02
IHD	2098.85	1014.72	290.84	154.63	1808.02	877.57
2010						
Control	2045.69	1029.12	281.10	152.55	1764.59	893.99
BI-MST	2101.92	1000.31	275.57	143.30	1826.36	872.59
MST	2078.55	1033.94	268.89	148.40	1809.66	901.87
IHD	2061.99	1011.11	262.30	140.92	1799.69	886.31

Multinomial Logit Model Description[67]

The multinomial logit model is used in unordered choice situations. The model is motivated by a random utility model, where the utility associated with choice j for consumer i is:

$$U_{ij} = \boldsymbol{x}'_i\boldsymbol{\beta}_j + \varepsilon_{ij}$$

where $\boldsymbol{x}_i$ is a vector of individual characteristics and β_j the choice-specific coefficients. Consumer i will choose alternative j (from J choice alternatives) if it corresponds with the highest utility level, and the multinomial logit model is motivated by the probability of this choice:

$$\text{Prob}(U_{ij} > U_{ik}) \quad \forall j \in J; j \neq k$$

Assuming that the J disturbances (ε_{ij}) are independent and identically distributed with a Gumbel (type 1 extreme value):

$$F(\varepsilon_{ij}) = \exp(-\exp(-\varepsilon_{ij}))$$

gives the multinomial choice model (where Y_i is a random variable indicating the choice):

$$\text{Prob}(Y_i = j|\boldsymbol{x}_i) = P_{ij} = \frac{\exp(\boldsymbol{x}'_i\boldsymbol{\beta}_j)}{1+\sum_{k=1}^{J}\exp(\boldsymbol{x}'_i\boldsymbol{\beta}_k)}$$

The J log-odds ratios are then:

$$\ln\left[\frac{P_{ij}}{P_{ik}}\right] = \boldsymbol{x}'_i(\boldsymbol{\beta}_j - \boldsymbol{\beta}_k)$$

The model is estimated by maximum likelihood (see Greene (2008)).

[67] This follows Greene (2008).

Figure B.1: EU Efficiency Labelling for Dryers

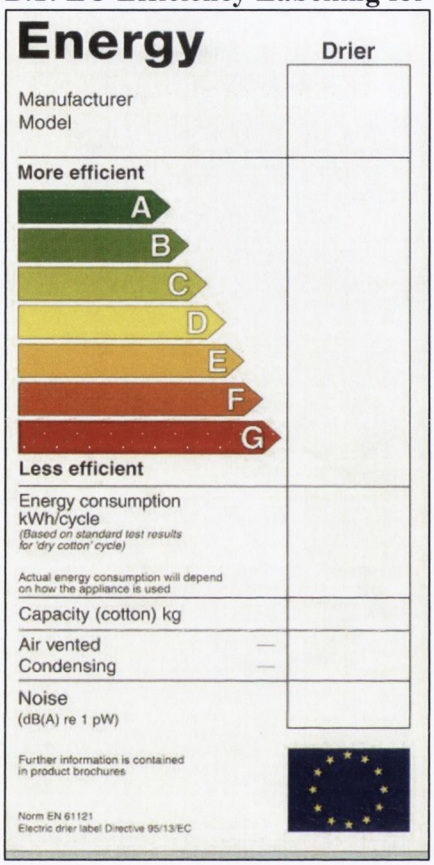


Table B.1: Characteristics of Dryers

Model	Vented	EU rating	Capacity	Price	Digital	Timer	Large porthole	Drying Sensor	Reverse Action	Delay start	kwh/ cycle	kWh/ annum
1	No	B	7	419.99	No	No	Yes	Yes	No	No	4.2	480
2	No	B	7	419.99	No	No	No	No	No	No	3.9	446
3	Yes	C	7	389.99	No	Yes	No	Yes	No	No	3.9	446
4	No	A	7	699.99	Yes	Yes	Yes	Yes	No	No	1.9	217
5	Yes	C	8	244.99	No	No	Yes	No	No	Yes	4.5	450
6	No	B	9	264.99	No	No	Yes	Yes	Yes	Yes	5.05	449
7	Yes	C	8	219.99	No	No	Yes	Yes	No	Yes	4.5	450
8	No	C	9	269.99	No	No	Yes	No	No	No	5.76	512
9	No	A	8	649.99	Yes	Yes	Yes	Yes	Yes	Yes	2.1	210
10	Yes	C	8	289.99	Yes	Yes	Yes	Yes	Yes	Yes	4.5	450
11	Yes	C	8	289.99	No	Yes	No	Yes	No	Yes	4.5	450
12	No	B	9	349.99	No	No	No	No	No	No	5.05	449
13	No	C	8	339.99	No	No	No	No	No	No	5.12	512
14	No	C	8	299.99	No	No	No	No	No	No	5.12	512
15	No	C	7	249.99	No	No	No	No	No	No	4.48	512
16	No	C	8	259.99	No	No	No	No	No	No	5.38	538
17	Yes	C	7	199.99	No	No	Yes	No	Yes	No	3.98	455
18	Yes	C	6	179.99	No	Yes	No	No	No	No	3.3	440
19	No	B	8	399.99	No	Yes	Yes	Yes	No	Yes	4.48	448
20	No	C	7	249.99	No	No	No	No	No	No	4.4	503

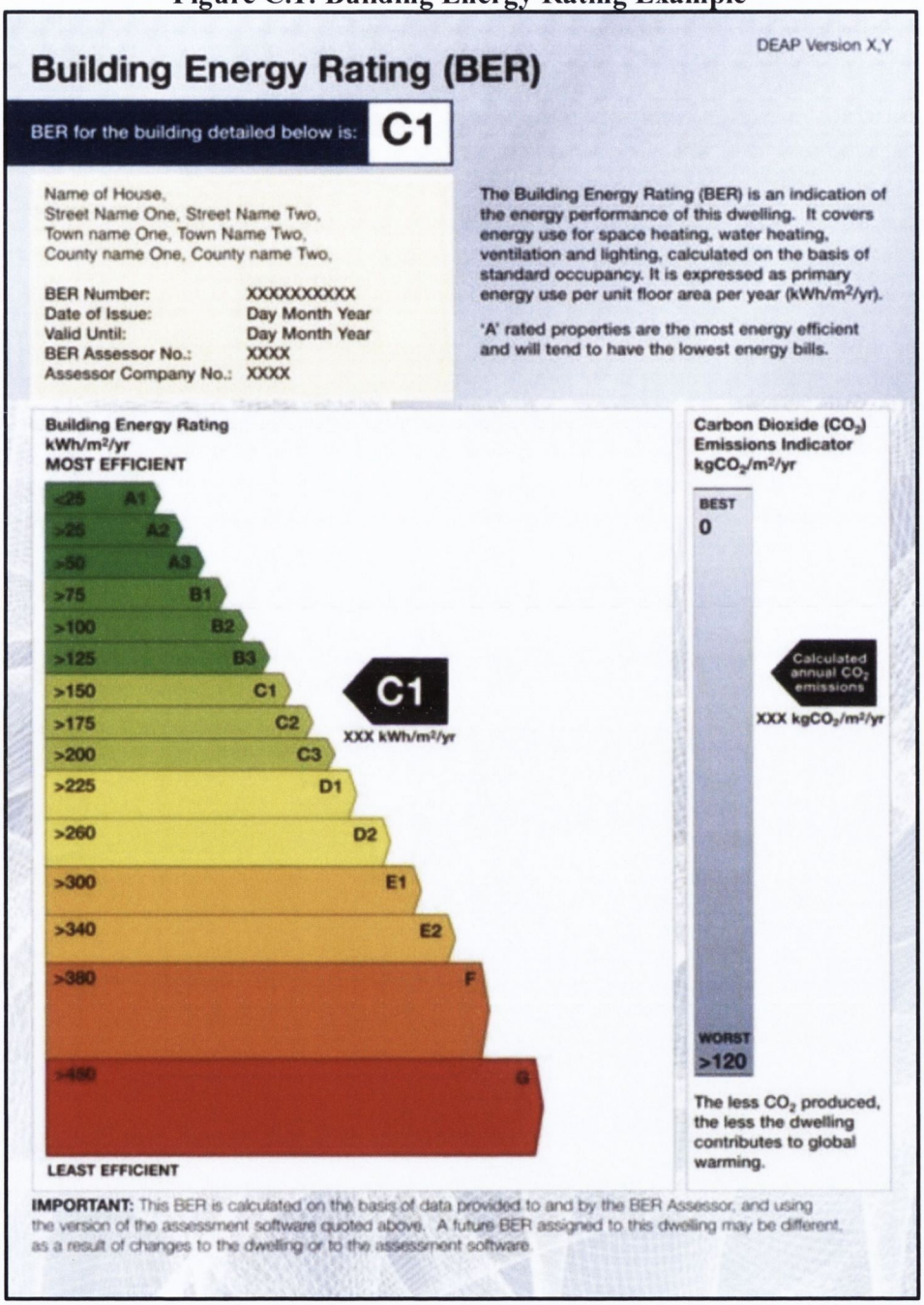
Table B.2: Area Characteristics

	T1	T2	T3	T4	T	S
Principal Economic Status:						
At work	59.12%	38.22%	49.30%	60.01%	51.50%	50.08%
Looking for first regular job	0.84%	1.50%	0.46%	1.23%	1.09%	0.95%
Unemployed having lost or given up previous job	7.11%	17.68%	4.77%	9.24%	10.21%	10.83%
Student	12.13%	9.79%	15.53%	8.09%	10.53%	11.33%
Looking after home/family	7.93%	11.08%	9.49%	7.18%	8.81%	9.42%
Retired	10.53%	14.34%	18.46%	11.49%	14.10%	12.67%
Unable to work due to permanent sickness/disability	2.10%	7.09%	1.63%	2.53%	3.46%	4.35%
Other	0.24%	0.31%	0.37%	0.23%	0.29%	0.37%
Education Level:						
No Formal Education	0.53%	2.74%	0.40%	1.12%	1.36%	1.41%
Primary Education	5.96%	29.00%	5.21%	6.99%	12.33%	13.80%
Lower Secondary	10.65%	25.31%	8.65%	9.87%	13.63%	16.63%
Upper Secondary	21.44%	17.53%	20.01%	18.16%	18.48%	20.03%
Technical or Vocational qualification	8.19%	7.30%	6.25%	7.78%	7.25%	8.61%
Advanced Certificate/Completed Apprenticeship	5.10%	3.26%	3.54%	5.28%	4.28%	5.72%
Higher Certificate	6.17%	1.83%	5.10%	5.04%	4.21%	4.50%
Ordinary Bachelor Degree or National Diploma	10.89%	1.78%	11.09%	9.78%	8.02%	7.39%
Honours Bachelor Degree, Professional qualification	14.01%	1.96%	17.80%	15.14%	12.37%	9.03%
Postgraduate Diploma or Degree	11.70%	1.14%	17.53%	12.73%	10.95%	7.48%
Doctorate (PhD) or higher	0.97%	0.05%	2.25%	1.09%	1.12%	0.73%
Not stated	4.39%	8.10%	2.18%	7.00%	6.01%	4.66%
Social Class:						
Professional workers	10.03%	1.02%	17.04%	8.84%	8.91%	7.34%
Managerial and technical	38.37%	11.65%	44.04%	33.47%	30.37%	27.28%
Non-manual	19.50%	16.00%	15.61%	17.79%	16.72%	17.46%
Skilled manual	10.94%	19.00%	6.44%	11.59%	12.23%	15.42%
Semi-skilled	7.10%	14.72%	3.95%	8.69%	9.06%	10.62%
Unskilled	1.70%	6.63%	1.01%	2.68%	3.31%	3.71%
All others gainfully occupied and unknown	12.35%	30.98%	11.91%	16.93%	19.41%	18.17%

Note: 'T1'-T4' indicate treatment stores 1-4 (Lucan, Finglas, Stillorgan and Blanchardstown respectively), 'T' indicates overall treatment (treatment stores combined) and 'S' indicates State figures. Data is downloaded from www.cso.ie (census of population) and treatment store areas are based on CSO Dublin parish classifications. Social Class is based on all individuals. Principal Economic Status and Education are based on individuals over 15 years old.

Appendix C – Paper 3 Supplementary Information

Figure C.1: Building Energy Rating Example



Note: Downloaded from the Sustainable Energy Authority of Ireland Website (www.seai.ie)

Figure C.2: Survey Screenshot – Attribute One

1 (of 6):



DISTANCE TO WORK/COLLEGE (time by public transport)
- will be one of the following...

10 minutes	30 minutes	60 minutes

Figure C.3: Survey Screenshot – Attribute Two

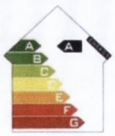
2 (of 6):

CONDITION (age of appliances, furniture and decoration)
- will be one of the following...

10 years old	5 years old	Brand New

Figure C.4: Survey Screenshot – Attribute Three (SAMPLE A)

3 (of 6):



The BER (the building energy rating)
- will be one of the following...

BER A	BER B	BER C	BER D	BER E	BER F	BER G
0-75 kWh/m²/yr	75-150 kWh/m²/yr	150-225 kWh/m²/yr	225-300 kWh/m²/yr	300-380 kWh/m²/yr	380-450 kWh/m²/yr	450+ kWh/m²/yr

Note: The BER is an indication of the energy performance of this dwelling. It covers energy use for space heating, water heating, ventilation and lighting, calculated on the basis of standard occupancy. It is expressed as primary energy use per unit floor area per year (kWh/m²/yr). 'A' rated properties are the most energy efficient and will tend to have the lowest bills.

Figure C.5: Survey Screenshot – Attribute Three (SAMPLE B)

3 (of 6):



Typical Energy Bill (2 months for heating, hot water and lighting)
- will be between...

€30 ⟷ €285

Note: These are average costs and will be higher in winter and lower in summer. The lowest cost apartments (the most efficient) have extremely high levels of insulation, triple glazed windows and the most efficient light bulbs and heating systems (access to solar panels, for example). Costs are based on normal use (thermostat set to 20 degrees) and calculated using the BER (building energy rating).

Figure C.6: Survey Screenshot – Attribute Four

4 (of 6):



AREA SAFETY (number of Public Order and Drug crimes per square kilometer):
- will be one of the following...

Low Crime Rate:	Average Crime Rate:	High Crime Rate:
40	70	110

Note: Based on official Garda Statistics for 2012

Figure C.7: Survey Screenshot – Attribute Five

5 (of 6):



RENT (€ per month)
- will be one of the following...

€800	€1000	€1200	€1400

Figure C.8: Survey Screenshot – Attribute Five

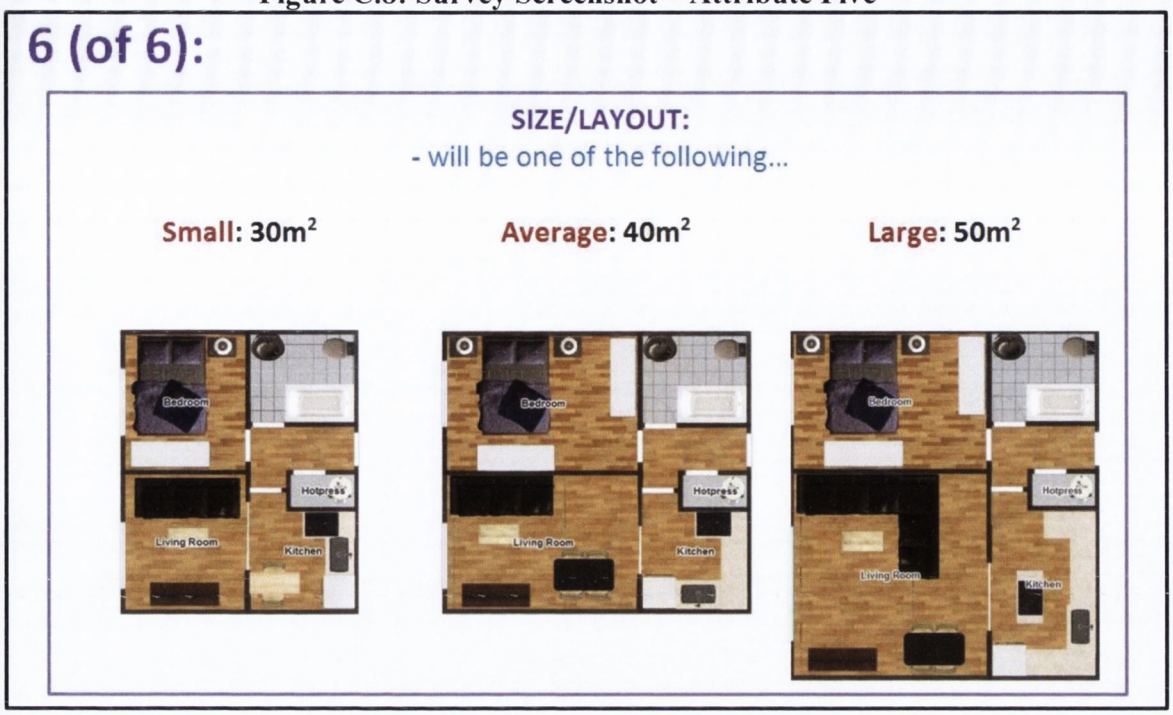


Figure C.9: Survey Screenshot – Choice Task Example

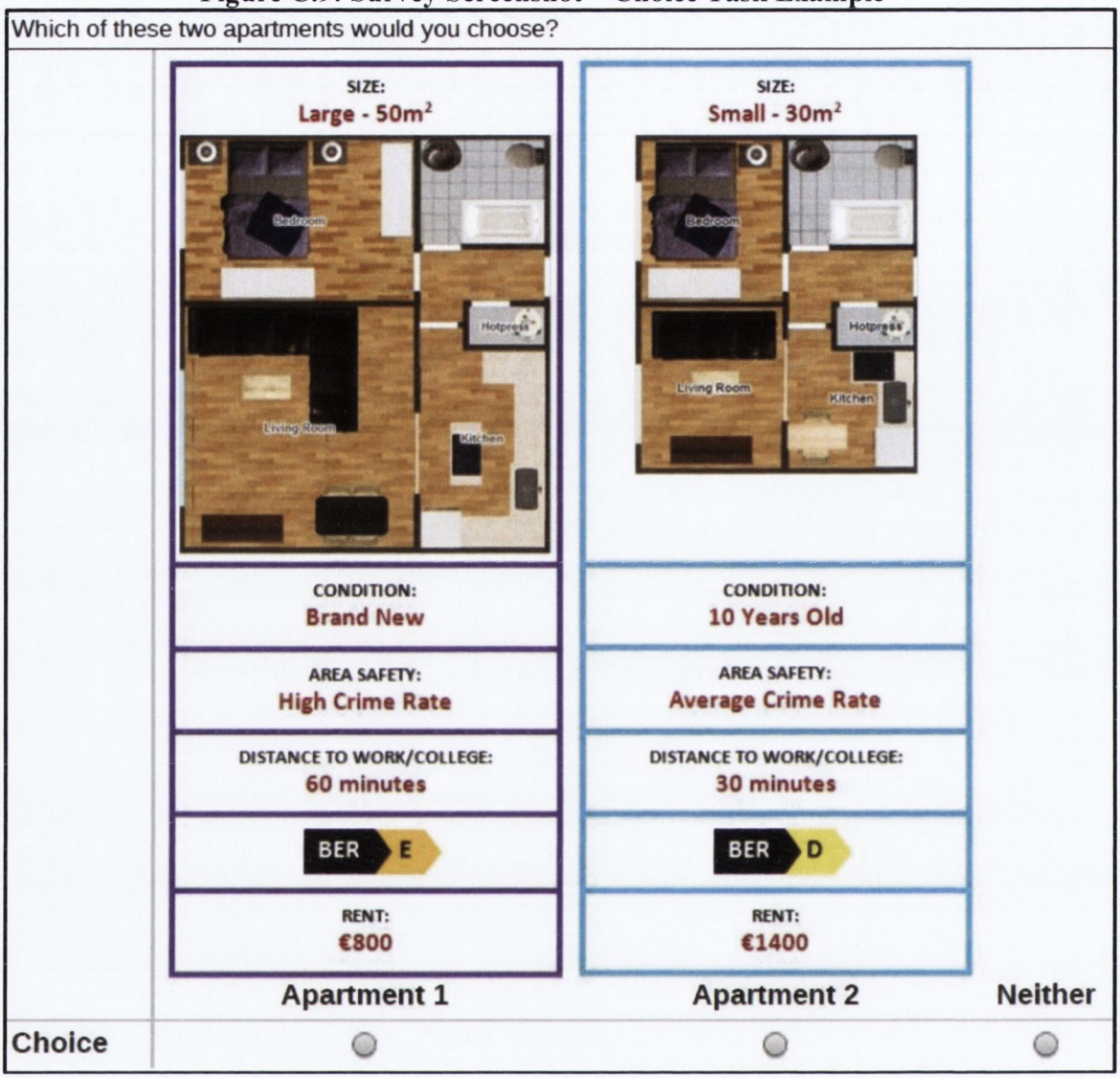


Table C.1: Experimental Design

		Apartment 1						Apartment 2					
block	choice	Size	Condition	Safety	Location	BER	Rent	Size	Condition	Safety	Location	BER	Rent
1	1	0	0	2	2	0	3	1	1	0	0	1	0
1	2	2	1	2	1	3	2	0	2	0	2	4	3
1	3	0	2	0	2	5	2	1	0	1	0	0	3
1	4	1	1	2	2	4	1	2	2	0	0	5	2
1	5	2	2	0	0	1	3	0	0	1	1	2	0
1	6	2	2	1	1	5	0	0	0	2	2	0	1
1	7	2	0	0	2	3	0	0	1	1	0	4	1
2	1	0	2	2	0	2	0	1	0	0	1	3	1
2	2	1	0	0	1	5	1	2	1	1	2	0	2
2	3	1	1	2	2	5	3	2	2	0	0	0	0
2	4	0	1	0	1	1	3	1	2	1	2	2	0
2	5	2	2	1	1	4	3	0	0	2	2	5	0
2	6	1	2	1	2	2	2	2	0	2	0	3	3
2	7	2	0	2	0	4	2	0	1	0	1	5	3
3	1	2	1	1	2	0	0	0	2	2	0	1	1
3	2	0	2	2	0	3	1	1	0	0	1	4	2
3	3	2	1	1	2	1	1	0	2	2	0	2	2
3	4	0	0	2	2	1	0	1	1	0	0	2	1
3	5	1	2	2	1	1	0	2	0	0	2	2	1
3	6	2	0	0	2	2	1	0	1	1	0	3	2
3	7	1	2	2	1	0	1	2	0	0	2	1	2
4	1	2	1	2	1	2	2	0	2	0	2	3	3
4	2	0	2	0	2	4	2	1	0	1	0	5	3
4	3	2	2	0	0	0	1	0	0	1	1	1	2
4	4	0	0	1	1	3	3	1	1	2	2	4	0
4	5	2	0	2	0	5	3	0	1	0	1	0	0
4	6	0	1	1	0	5	0	1	2	2	1	0	1
4	7	1	2	1	2	3	3	2	0	2	0	4	0

Note: Coding is as follows – Size (0 = small; 1 = medium; 2 = large), Condition (0 = 10 years; 1 = 5 years; 2 = brand new), Safety (0 = high crime; 1 = average crime; 2 = low crime), Location (0 = 60 minutes; 1 = 30 minutes; 2 = 10 minutes), BER (0 = F; 1 = E; 2 = D; 3 = C; 4 = B; 5 = A) and Rent (0 = €1400; 1 = €1200; 2 = €1000; 3 = €800

Table C.2: Sample Descriptive Statistics

	Mean	Std. Dev.
Age	27.23	7.05
Age cat. 1 (less than 20 years)	11.09	
Age cat. 2 (20 to 29 years)	63.97	
Age cat. 3 (30 to 39 years)	20.40	
Age cat. 4 (40 to 49 years)	3.22	
Age cat. 5 (50 to 59 years)	1.09	
Age cat. 6 (over 60)	0.23	
Income (net)	1336.10	983.22
Income cat. 1 (less than €500)	38.82	
Income cat. 2 (€500 to €1000)	18.15	
Income cat. 3 (€1000 to €1500)	13.65	
Income cat. 4 (€1500 to €2000)	8.41	
Income cat. 5 (€2000 to €2500)	10.25	
Income cat. 6 (€2500 to €3000)	5.76	
Income cat. 7 (€3500 to €4000)	2.25	
Income cat. 8 (€4000 to €4500)	0.69	
Income cat. (over €4000)	1.21	
Education cat. (Primary)	0.00	
Education cat. (Secondary)	37.64	
Education cat. (Degree)	28.22	
Education cat. (Masters)	21.55	
Education cat. (PhD)	12.59	

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The Role of Information in Household Energy Decisions

James Carroll

Abstract: *The economic rationale for informational demand-reducing policies is, in general, the presence of imperfect or asymmetric information – that missing information on behalf of market participants (the energy user or investor) is leading to a socially sub-optimal market equilibrium (a market failure), whether that be a less efficient technology choice at the point of sale or high energy-consuming behaviours post investment. Furthermore, this failure to choose more efficient energy-consuming products, not only increases energy demand, generation and environmental damage, but often represents a deviation from cost-minimising behaviour and therefore has a negative impact on private welfare. This dissertation explores the effects of three informational interventions in energy markets – smart metering, appliance energy cost labelling and property efficiency labelling – to highlight the underlying energy-reducing motivations of households and the presence of market failure. Within a smart metering trial, Paper 1 explores the role of knowledge improvements (related to energy-reducing behaviours) in electricity demand reductions. Results show that smart metering significantly improves a household's stock of energy-reducing knowledge, but that these improvements are not correlated with observed reductions in demand. Paper 2 tests the presence of household inattention to future energy costs by applying 'lifetime' energy cost labels to appliances (trial using tumble dryers). While an improvement in energy efficiency is observed (3% reduction in the mean energy consumption of dryer sales), this change is not statistically significant. Paper 3 explores the cause of low efficiency levels in rental markets and estimates the willingness-to-pay for energy efficiency improvements using a hypothetical choice experiment. Results show that renters will pay more for energy efficiency, but that the increase in rents will likely be too low to promote considerable energy efficiency investment by landlords. In general, the magnitudes of the effects explored suggest that information, independently, is likely to play a minor role in future energy demand reductions, given the scale of abatement targets. Information, however, could become more important in the future with rising energy prices and increased household motivation to reduce.*