ABSTRACT

Title of dissertation: EFFECTS OF INFORMATION AND TIME-OF-USE PRICING ON IRISH ELECTRICITY DEMAND AND SUPPLY

Shirley Pon, Doctor of Philosophy, 2016

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In this dissertation I quantify residential behavior response to interventions designed to reduce electricity demand at different periods of the day.

In the first chapter, I examine the effect of information provision coupled with bimonthly billing, monthly billing, and in-home displays, as well as a time-of-use (TOU) pricing scheme to measure consumption over each month of the Irish Consumer Behavior Trial. I find that time-of-use pricing with real time usage information reduces electricity usage up to 8.7 percent during peak times at the start of the trial but the effect decays over the first three months and after three months the in-home display group is indistinguishable from the monthly treatment group. Monthly and bi-monthly billing treatments are not found to be statistically different from another. These findings suggest that increasing billing reports to the monthly level may be more cost effective for electricity generators who wish to decrease expenses and consumption, rather than providing in-home displays.

In the following chapter, I examine the response of residential households after exposure to time of use tariffs at different hours of the day. I find that these

treatments reduce electricity consumption during peak hours by almost four percent, significantly lowering demand. Within the model, I find evidence of overall conservation in electricity used. In addition, weekday peak reductions appear to carry over to the weekend when peak pricing is not present, suggesting changes in consumer habit.

The final chapter of my dissertation imposes a system wide time of use plan to analyze the potential reduction in carbon emissions from load shifting based on the Ireland and Northern Single Electricity Market. I find that CO2 emissions savings are highest during the winter months when load demand is highest and dirtier power plants are scheduled to meet peak demand. TOU pricing allows for shifting in usage from peak usage to off peak usage and this shift in load can be met with cleaner and cheaper generated electricity from imports, high efficiency gas units, and hydro units.

EFFECTS OF INFORMATION AND TIME OF USE PRICING ON IRISH ELECTRICITY DEMAND AND SUPPLY

by

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Dedication

I dedicate this manuscript to my grandmother.

Acknowledgments

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List of Abbreviations

α	alpha
β	beta
CER	Commission for Energy Regulation
CPP	critical peak pricing
IHD	in-home display
SEIA	Sustainable Energy Authority of Ireland
SEM	Single Electricity Market
TOU	time-of-use pricing

Chapter 1: Overview

In most countries, households use electricity and pay for it only at the end of the billing cycle one or more months later. The disconnect between the time-of-use (TOU) and the time of payment is sometimes blamed for the little awareness and/or wastefulness that many consumers appear to have about their usage of electricity. Real time information feedback combined with various pricing schemes has been found to reduce residential energy consumption more than information and pricing policies alone [22, 28, 31]. Within this manuscript, I present three chapters linked by the commonality of how information and TOU pricing are utilized in in an effort to curtail peak usage, as well the impact on environmental quality. Specifically, I examine several research questions that explore the use of various forms of information provision to encourage residential households to engage in energy conservation and load shifting. First, in the context of information provision, I analyze the effect of how increased frequency of information impact customer consumption patterns. Then, I examine the potential changes in habit in response to TOU billing and heterogeneity in such responses. Finally, I apply a hypothetical systemwide TOU policy to analyze potential savings in generation and CO_2 emissions.

In the first two chapters, I utilize a unique dataset from the Irish Consumer

Behavior Trial to examine the effect of information provision on consumption. The trial took place between 2009 and 2010 when Irish households that were previously on a flat rate tariff and bi-monthly billing were invited to participate in a TOU trial. Households selected to be in the treatment group receive their usage information in bi-monthly billing, monthly billing, or in-home displays. Socio-demographic information such as age, education, house type, homeownership, and employment was collected through pre and post trial surveys.

In the first chapter, the main method of estimation is a panel fixed effects model to estimate the information treatment effects with monthly interaction terms. Results suggest that monthly and bi-monthly billing do not provide significantly different results. I suspect that households with less educated and older residents are more likely to drop out of the treatment group. To correct for possible self-selection out of the trial, I apply fixed effects and a method called coarsened exact matching where households in the treatment and control group are matched by household characteristics such as age, education, and type of residence. Results from robustness checks show similar results.

Second, I examine the response of residential households at different hours of the day to the introduction of TOU tariffs. TOU pricing encourages households to alter their electricity consumption patterns. Again, I apply a panel fixed effects model to hourly observations to estimate the average hourly response to TOU pricing for weekdays and weekends. Results are consistent with expectations: households shift usage away from peak periods in order to consume electricity at a lesser tariff rate. I posit that households with the highest demand would be most responsive to

TOU treatment. Households in the lowest quantile of demand appear to increase their overall consumption in response to TOU pricing. Since poor households tend to have low electricity usage, an increase in the consumption on TOU pricing may indicate an improvement in comfort.

In the final part of my dissertation, I impose a systemwide TOU plan to analyze the potential reduction in carbon emissions from load shifting based on the Ireland and Northern Ireland Single Electricity Market. I utilize generator unit commercial and technical offer data to create daily merit curves representative of the island electricity supply. I calculate the cost of generation and subsequent CO_2 emissions from generation for actual load demand. I apply the same procedure to a situation under which residential TOU pricing is imposed on the island based on average treatment effect results from the previous chapter. Findings suggest that TOU pricing during fall and winter months provide the largest emissions savings. I do not find evidence of an increase in emissions that has been found with systems that use hydro and oil units to meet peak load.

Chapter 2: The Effectiveness of Information Provision with Time-of-Use Pricing

2.1 Introduction

Feedback on electricity use has been found to be an effective mechanism in improving supplier efficiency and encouraging the reduction of residential energy consumption [28, 35]. One way these savings have been made possible through the widespread installation of smart meters in the US and European countries such as the UK, Italy, and France [30]. In this paper, a smart meter is defined as a device that records a households incremental energy usage and transmits the information to inform the utility of periods of high and low electricity demand in real time.[1] The consumer is able to access information about his/her real time electricity usage and current tariff rate from an in-home display (IHD). This information can allow the consumer to learn about how their energy habits impacts their overall usage and

[1]Darby (2006) defines meters with one-way customer to utility communication abilities to be automated meter reading meters. These meters require additional technology, such as IHDs or web applications, in order for consumers to receive real time information. The general literature defines smart meters as devices that are capable of transmitting information two ways between the utility and consumer [22].

bill and encourage conservation practices.

Utilities often use energy efficiency and demand response programs, such as time-of-use (TOU) pricing and dynamic pricing (e.g. real time pricing and critical peak pricing (CPP)), to reduce electricity demand and shift peak usage. These pricing schemes allow the price of electricity to reflect the cost of generation at varying efficiency rates of fuel powered generation and fuel prices during times of high and low demand [20, 30].[2] The ideal result is a shifting of usage away from periods of higher energy costs to periods of lower energy cost and reduce greenhouse gas emissions when dirtier fuels or less efficient generation units are used to meet peak demands [30]. Other benefits of dynamic and TOU pricing include reducing peak congestion and susceptibility to outages by spreading out electricity demand to other periods and allowing for more efficiently generated electricity to be distributed to consumers [30, 62].

Under TOU pricing schemes, prices are higher during times of peak demand and lower during off peak periods. These price signals give consumers the incentive to reduce or shift their usage away from peak hours in exchange for lower bills. TOU pricing is commonly identified as a separate entity from dynamic pricing because the rate structure is known in advance and does not vary with system demand in an unpredictable fashion. This eliminates price uncertainty and enables customers to alter their habits around peak periods.

Determining how TOU and feedback information are adapted into the house-

[2] If the baseload is fueled with a more carbon intensive fuel, such as coal or fuel oil, then shifting peak load may result in an increase in CO_2 emissions.

hold and how households adjust their consumption over time would provide evidence about the effectiveness of continuous information provision. Although several studies look at the impact of feedback on household energy savings with various pricing strategies [26,51,68,78], how these feedback technologies compare with conventional billing methods have yet to be explored. To determine whether these feedback technologies are cost-effective, it is necessary to assess if their effect is sustained over time.

The aim of this paper is to analyze the change in usage with different methods of information feedback coupled with a TOU pricing scheme. I use the Ireland Behavior Trial data (Di Cosmo et al. 2014, Caroll et al. 2014). The Commission of Energy Regulation conducted the trial in 2009-2010 to investigate the impact of smart metering technology combined with TOU pricing and information stimuli on consumer behavior during times of peak demand. I take advantage of this unique panel with information about household electricity consumption to answer three main questions on the effectiveness of an IHD compared to the conventional methods of billing.

First, how persistent are the effects of information provision in a TOU setting? One potential interpretation is that the increased stock of information treatment allows households to learn about their usage patterns and adapt their usage around peak periods to increase savings. This learning occurs through consumer experimentation by altering daily habits such as turning off lights, unplugging electronic devices, lowering the thermostat if the home uses electric heating, and waiting until off peak times to start running appliances. Households can determine which actions impact their electricity bill the most and optimize their usage. Alternatively, the treatment can act as a cue that reminds consumers to cut back on their usage, which may persist for as long as the treatment is in place, or longer.

Second, how do households with IHDs compare in terms of peak energy savings to those on monthly or bi-monthly billing in the beginning and the later months of the trial? In other words, what is the benefit gained from additional information? On average, a household with an IHD is expected to have a larger response than a household with conventional billing as they have more complete information sets. However, information provision has been found to affect households in a heterogeneous manner. While households are able to save on average, some increase their usage with monitoring [68]. And, having the IHD doesnt mean that you necessarily use it.

And third, what are the overall savings from households with IHDs compared to conventional billing? This question is tied to the previous question in that households with more information are expected to make larger changes to their energy use. Yet, it may be possible that households with extremely low usage may increase their usage overall when provided with more information [35]. Given the structure of TOU pricing, gains in reduced peak consumption may be offset by increases in off peak consumption. This question addresses the overall energy conservation aspect of information with TOU pricing.

Multiple studies have found that information with pricing policies reduce or shift energy consumption by encouraging behavioral changes [16, 26, 31, 51–53, 78]. Other studies find time varying pricing to be more effective with critical peak pricing and load controls [79, 80]. In this paper, I find that households with IHDs on a bi-monthly billing schedule reduce their peak energy consumption by a larger percentage than households in the monthly and bi-monthly treatment groups during the earlier months of the trial. However, the IHD reductions decline until the effects are comparable to those of monthly billing. The fading of the effects suggests that IHD reductions are not permanent but become less effective over time as households become accustomed to the IHD. On the other hand, monthly and bi-monthly treatment groups show gradual increase in reductions over the course of the trial, suggesting a slower learning rate as households develop a new habit stock. In terms of overall conservation I find that monthly billing is more cost effective than providing IHDs with a 10-year lifespan.

The remainder of this paper is organized as follows: Section 2 provides a discussion of relevant literatures, Section 3 discusses the background of the Irish electricity market, Sections 4 and 5 discuss the trial design and provides a description of the data. Section 6 explains the models and provides an analysis of the results. Section 7 provides a brief cost comparison and section 8 concludes.

2.2 Relevant Literature

Energy is infrequently on the mind of the typical consumer and increasing information transparency in energy usage can nudge consumers to be more conscious of their consumption by encouraging the adoption of energy efficiency and conservation practices [14, 35, 39]. Providing households with information on their usage may increase awareness of their energy consumption and enable learning and experimentation with their energy usage to potentially increase energy savings by 7-12 percent [56]. Gans et al. (2013) shows that households on a prepaid plan reduce their average by 11 to 17 percent when given keypad technology meters that displayed real time usage information. Similarly, Houde et al. (2013) finds that households with access to direct feedback through a Google operated web application had an average reduction of 5.7 percent in energy usage in the mornings and the evenings.

In addition, the combination of information with pricing policies is more likely to encourage further reduction in usage since feedback may become less effective when it becomes more difficult for households to reduce their consumption after a certain point without additional incentives [9, 40, 54]. Addressing the behavior of consumers to change their energy usage may play a larger role in the success of an IHD than environmental awareness alone [37].

Past literature has studied the effects of information provision and found that information and pricing policies alone result in lower energy savings than what is found in studies that combined information and dynamic pricing schemes [22,28,31]. Jessoe and Rapson (2013) find households on CPP combined with IHDs were able to consistently reduce their consumption by 10 percentage points more than households with CPP only. Similarly, Ivanov et al. (2013) find that households with smart meters and smart thermostats use 15 percent less energy than those without enabling technologies on critical peak days. Ito et al. (2013) analyze a trial in Japan where every household receives an IHD and find the impact of critical peak pricing to be more effective than social pressure, suggesting pricing policies provide further incentive than conservation alerts.

TOU pricing in conjunction with information has been found to result in the shift of usage around peak times. Torriti (2012) compares electricity consumption one year before and one year after the introduction of TOU tariffs and finds that households shift their usage during peak hours to the hours directly prior and after the peak period, demonstrating consumers ability to change their habits by starting their appliances at earlier or later times. His overall findings suggest an increase in usage by 13.69 percent but billing amounts decreased by 2.21 percent, questioning the effectiveness of IHDs with TOU pricing. This study, however, did not include a control group to account for trends that may confound the estimation.

Other studies that have utilized the Ireland Consumer Behavior Trial data used in this paper have found IHDs to effectively reduce consumption during peak period under a TOU policy. Di Cosmo et al. (2014) estimate a difference-in-differences (DID) random effects panel regression to determine presence of a linear relationship between the size of the TOU tariff applied and the reduction in electricity consumed. They find households installed with IHDS exhibit a weak price response associated with the applied TOU during peak hours. Alternatively, households on monthly and bi-monthly billing are associated with nonlinear responses to changes in TOU tariff, consistent with non-linear reactions observed in Reiss and White (2005) and Woo et al. (2013b).[3] Caroll et al. (2014) aggregates pretrial and testing period consumption

[3] Woo et al. (2013b) also estimates the elasticity of substitution from peak to off peak usage

to two observations per household to estimate a DID fixed effects model. They find peak reductions of 9.4 percent for households with IHDs, 8.7 percent for households on monthly billing, and 5.4 percent for households on bi-monthly but do not find evidence that increasing information provision to have an effect on reducing peak consumption.

I study the persistence of energy savings of different information feedback to determine if more information is cost effective. I find a gradual increase in savings from conventional billing methods and a dramatic decrease in IHD treatment effects after three months of the trial. Ultimately, I test the difference between treatments and find the effects are not significantly different from another in the latter parts of the trial.

These findings regarding consumer learning from information and conventional billing methods are similar to studies in other areas of research that find evidence of consumers learning from bills. For example, participants who fill out overdraft surveys are less likely to incur overdraft fees [10, 71]. Another study analyzed participants switching calling plans to minimize cost of service [59]. Narayanan et al. (2007) find consumers on fixed telephone plans learn slower than consumers on variable plans as the latter provided more information on their usage. Some studies have found that treatments like this require persistence in information provision. Houde et al. (2013) finds the effects in their trial begin to fade by the fourth week

to be less than 0.07 for TOU pricing without information. This estimate indicates a low response compared to estimates in Baladi et al. (1998) who find the elasticity of substitution to be 0.14 for a typical home, 0.39 for all electric homes, and -0.006 for homes without major electric appliances.

after their trial terminated. Behavior formed over a three-month period is likely to persist but only with continued feedback [22].[4]

In this paper, the treatment group provided with real time information is associated with high reductions in usage but decays as the trial advances. This suggests that effectiveness of information wanes when households get used to the presence of the display. Examples of this can be found in other facets of consumer research. Richins and Bloch (1991) find that car owner involvement with their vehicle diminishes as they grow accustomed to their purchase. After the initial novelty of their purchase subsides, consumers dont spend much time thinking, learning, or talking about the product on a day-to-day basis [65] . Similarly, the shock of the home energy reports and bills aimed to generate an immediate response in energy reduction have been found to decay over the days following the report arrival [8,38]. Evidence of reduced effectiveness of signals can also be found in medicine where the effectiveness of mailed appointment reminders seemed to decrease with time [60].

2.3 Background

2.3.1 Residential Electricity Consumption in the Republic of Ireland

Home heating consists of a significant proportion of energy consumed in residential homes in the Republic of Ireland, where 67 percent of residential energy consumed goes towards space heating and 16 percent to water heating [72]. The

[4]The Houde et al. (2013) trial spans a period of three months, March through May 2010.

late development of a natural gas network makes fuel oil their main source of energy followed by electricity and natural gas. Fuel oil (40.6 percent in 2010) and natural gas (38.6 percent) are the fuels predominantly used for residential space heating; electricity constitutes a mere 4.8 percent. Government programs have aimed to reduce energy usage and CO2 emissions by providing incentives for households to adopt energy efficient measures.[5]

Since Ireland is a country that does not rely on electricity for heating and cooling, energy savings must come from other end uses. In 2011, the major end use of electricity is hot water heating with electric immersion (25 percent), followed by small appliances such as computers and televisions (19 percent). Lighting constitutes as 16 percent of electricity usage, washers and dryers 11 percent, and refrigeration 10 percent [72]. The rest goes towards cooking, fans, and space heating. Shifting of usage can come from waiting until the off peak period to use hot water, run the washers and dryers. Turning off lights and small appliances when not in use can result in overall electricity savings. Savings can also occur through efficiency gains when households replace old appliances with more efficient ones (e.g. a new clothes washer uses 70 percent less energy [63].

[5]Some recent programs include the Home Energy Saving Scheme, which started in 2008 and was integrated into the Better Energy Homes Scheme in 2011. The Better Energy Homes Scheme provided grants totaling up to 160 million Euros and saved 47 million Euros on energy costs [72].

2.3.2 Electric Ireland, Meter Readings, and Smart Meters

The full deregulation of the electricity market in 2005 allowed electricity customers across Ireland to choose their suppliers. Prior to this, the state-owned company Electric Ireland supplied all domestic electricity. Around the time of the Ireland smart meter rollouts in 2008, Electric Ireland continued to supply electricity to 100 percent of the market in Ireland. The company conducted meter readings four times a year and required a meter reader to be physically present at the home to record the meter reading. If the reader was unable to get a reading then the utility used an estimate until the next reading occurred and adjusted the bill accordingly. Customers received their electric bills every two months that included the meter reading and the tariff applied to the bill [2].

The conventional method of meter reading is more prone to errors in supplier services and billing caused by inaccurate readings from human error or estimation errors if a current reading is not possible. Properly functioning smart meters eliminate these errors by providing accurate and real time readings in 15 minute to hourly intervals. In this trial, smart meters record the households usage at half hourly intervals and transmit this information to the supplier and households with IHDs.[6]

[6] Smart meter installation does not automatically imply that consumers are given feedback. Recorded usage information is generally provided to the supplier and an additional display unit is required for households to gain access to the smart meter information.

Pre-Benchmark Period March 2008-June 2009	Benchmark Period July-December 2009	Trial Period January-December 2010	Post-Testing Period January-February 2011
• Smart meter installation • Recruitment in 4 waves • Non-recruitment survey	• Collection of baseline consumption data • Pre-trial survey • Treatment group on calendarized billing • Treatment group receive balancing credit	• Treatment groups information and TOU tariffs • Control group on bi-monthly billing cycles and flat rate tariff	• Post-trial survey • Treatment group returns to regular bi-monthly billing cycle and flat rate tariff • Treatment group receives balancing credit

Figure 2.1: Trial Timeline

2.4 Trial

The Commission of Energy Regulation conducted the Irish Consumer Behavior Trial as part of the National Smart Metering Plan in the Republic of Ireland. The trial took place from 2009-2010 to investigate the impact of smart metering technology combined with TOU tariffs and feedback stimuli on consumer behavior on reductions in peak demand and overall electricity use [20].

Figure 2.1 outlines the timeline of the trial:

- Pre-Benchmark period (Mar 2008-June 2009): Recruitment of participants occurred in four waves where subsequent waves are adjusted to ensure a nationally representative sample. An additional non-recruitment survey is conducted to ensure that those who did not participate in the trial were not significantly different from those who were. During this period, smart meters are installed in participating homes.

- Benchmark period (July-Dec 2009): Baseline data are collected prior to the start of the test period and the billing period post is adjusted to the calendar month. Consumers receive bi-monthly electric bills. The pre-trial survey is also conducted and participants are randomly assigned to control and treatment groups. The treatment group receives the first half of their balancing credit.[7]

- Testing period (Jan-Dec 2010): The control group continues to be billed at their existing flat rate (14.1 cents per kWh) and receive a bi-monthly electric bill whereas the treatment groups have different TOU tariffs and feedback stimuli.

- Post trial survey (Jan-Feb 2011): Participants return to their normal billing cycle and flat rate tariffs on January 1, 2011. The post trial survey is conducted via telephone during this period. The treatment group receives the second half of their balancing credit.

[7]Prior to the start of the trial, households were also guaranteed a balancing credit to ensure they do not incur more costs than if they were on the regular tariff. The credits were distributed in December 2009 and January 2011 to avoid any unintended effects to household consumption during the trial. See Tables A.1 and A.2 in Appendix A for details about households that received the credit. Approximately 41 percent of households in the treatment group received balancing credits. A larger proportion of the bi-monthly group received balancing credits, followed by the monthly group. This means that households on the trial not on the IHD were not reducing/redirecting their usage enough to avoid paying more than if they were on the flat tariff. They therefore had to be compensated.

Treatment	Night 11pm-7:59am	Day1 8am-4:59pm	Peak 5pm-6:59pm	Day2 7pm-10:59pm	Flat Rate
Tariff A	12	14	20	14	
Tariff B	11	13.5	26	13.5	
Tariff C	10	13	32	13	
Tariff D	9	12.5	38	12.5	
Control					14.1

Table 2.1: Weekday TOU Pricing Schedule (Euro cents per kWh excluding VAT)

At the time of assignment to treatment, the trial had 5,027 participants who volunteered to participate in the trial, of which 1,170 were randomly assigned to the control group. Records were deleted from the study for participants who withdrew from the trial. Of the original sample, 2,407 remain in the treatment group and 928 in the control group for the study.[8]

Participants in the Residential group are randomly assigned two treatments. The first treatment is the TOU tariff where each household is assigned to one of four TOU pricing structures in Table 2.1. The TOU day is divided into the following periods: peak period from 5pm-6:59pm on weekdays, day periods are between 8am-4:59pm and 7pm-10:59pm on weekdays and 8am-10:59pm on weekends and holidays (the peak period is excluded from weekends and holidays), and the night period (off peak hours) are the hours between 11pm-7:59am. The prices of electricity during these hours are structured with the peak having the highest tariff when demand for

[8]Participants were assigned to two TOU tariff groups, a Residential Tariff and a Weekend Tariff. Participants from the Weekend tariff are omitted from this study (100 households) as they face a different pricing structure from the Residential Tariff group. An additional information treatment group also omitted from the study (939 households).

Treatment	Description
BM	Bi-monthly billing + energy report
M	Monthly billing + energy report
IHD	In-home display + bi-monthly billing + energy report
Control	Bi-monthly billing

Table 2.2: Information Treatment

	BM	M	IHD	Control	Total
Tariff A	281	290	293	-	864
Tariff B	108	111	114	-	333
Tariff C	299	295	291	-	885
Tariff D	109	114	103	-	325
Control	-	-	-	928	928
Total	796	810	801	928	3,335

Table 2.3: Treatment Assignment

electricity is highest and off peak having the lowest tariff when demand is lowest. Tariff A has the highest nighttime rate but has the lowest peak rate. Tariff D, on the other hand, has the lowest nighttime rate and the highest peak rate.

The second treatment assigns each household one of three feedback groups that provide varying degrees of feedback on information about their energy usage, as shown in Table 2.2.[9] All three information feedback groups receive a billing statement combined with an energy usage statement providing details on their household electricity usage along with tips on how to reduce energy use. The first group receives bi-monthly (BM) electricity bills with the first bill arriving in March. The second group receives bills on a more frequent monthly (M) basis. The last group has an IHD (IHD) in addition to receiving a bi-monthly bill. The IHD relays real

[9] A fourth information stimulus included a bi-monthly bill with an Overall Load Reduction incentive of 20 Euros if households are able to reach a 10 percent reduction target over a period of 8 months. This group had a later start date than the other treatments and is excluded from the analysis.

time information, which is information updated at 30-minute intervals to the participants that includes the households electricity usage, associated cost of electricity consumed, and current price of electricity.[10] Appendix A provides information about the in-home display and shows a picture of one. A budget setting mechanism is also included into the monitor to allow households to decide their maximum spending on electricity per day. Table 2.3 shows the distribution of the TOU tariff and information treatment assignments.

Participants completed pre- and post-trial surveys that gathered socio-demographic data about the respondent and household. Questions include respondents age, gender, employment, income bracket, size of the home, number of people residing in the home, and types of fuel used for heating and cooking. A majority of the questions in the second half of the survey assess usage behavior during the trial. The post-trial survey gathered information on respondents perception of the impact of the trial, tariffs and method of information feedback. The survey also asks after the ownership and replacement of appliances and if participation in the trial resulted in more energy efficient investments. Attitudes towards energy reduction were also included in the survey.

[10]The post trial survey did not inquire about the frequency of interaction with the IHD. Of the 622 IHD respondents that completed the follow up survey, 49.36 percent regularly and 22.35 percent occasionally continued to consult their display. Households that stopped using the display felt they had already learned as much as they could or didnt find the display useful (36.93 percent) while others claimed their display had stopped working (37.50 percent).

	Treatment		Control		T-C		p-value	T obs	C obs
Electricity Consumption									
Daily baseline mean (kWh)	12.08	(1.79)	11.46	(1.73)	0.62	(0.22)	0.01	123	123
Day1 baseline mean (kWh)	0.51	(0.07)	0.49	(0.07)	0.02	(0.01)	0.01	119	119
Peak baseline mean (kWh)	0.85	(0.20)	0.80	(0.18)	0.05	(0.02)	0.03	119	119
Day2 baseline mean (kWh)	0.78	(0.13)	0.74	(0.12)	0.04	(0.02)	0.02	119	119
Night baseline mean (kWh)	0.29	(0.02)	0.27	(0.02)	0.02	(0.00)	0.00	119	119
Demographics									
No. of residents	3.07	(2.21)	2.86	(2.20)	0.21	(0.09)	0.02	2731	768
No. of residents (> 15 years)	2.53	(0.98)	2.47	(0.93)	0.06	(0.04)	0.18	2232	596
No. of residents (< 15 years)	1.89	(0.93)	1.90	(0.97)	0.02	(0.08)	0.85	832	186
Age of respondent 18-35 (%)	11.00	(0.31)	9.46	(0.29)	10.66	(0.01)	0.21	2718	761
Age of respondent 36-55 (%)	46.98	(0.50)	41.79	(0.50)	5.20	(0.02)	0.01	2718	761
No formal education (%)	1.36	(0.12)	1.64	(0.13)	1.42	(0.01)	0.58	2582	731
Primary education (%)	10.88	(0.31)	15.32	(0.36)	4.44	(0.01)	0.00	2582	731
Secondary education (%)	47.13	(0.50)	47.61	(0.50)	0.47	(0.02)	0.82	2582	731
Third level education (%)	40.63	(0.49)	35.43	(0.48)	5.20	(0.02)	0.01	2582	731
Employed (%)	52.07	(0.49)	53.91	(0.50)	8.16	(0.02)	0.00	2731	768
Unemployed (%)	8.79	(0.28)	7.29	(0.26)	1.50	(0.01)	0.17	2731	768
Retired/caretaker (%)	29.15	(0.45)	38.80	(0.48)	9.66	(0.02)	0.00	2731	768
Housing Characteristics									
Homeowner (%)	92.99	(0.25)	93.34	(0.25)	0.36	(0.01)	0.73	2723	766
No. of bedrooms	3.47	(0.83)	3.42	(0.87)	0.05	(0.04)	0.16	2726	766
Apartment (%)	1.65	(0.13)	1.96	(0.14)	0.31	(0.01)	0.58	2726	766
Semi-detached home (%)	33.42	(0.47)	29.11	(0.45)	4.31	(0.02)	0.02	2726	766
Detached home/bungalow (%)	50.33	(0.50)	54.44	(0.50)	4.11	(0.02)	0.04	2726	766
Terraced home (%)	14.60	(0.35)	14.49	(0.35)	0.11	(0.01)	0.94	2726	766
No. of appliances^a	6.09	(1.90)	6.01	(1.91)	0.09	(0.08)	0.27	2731	768
No. of electronics^b	4.08	(2.30)	3.72	(2.23)	0.36	(0.09)	0.00	2731	768
Electric space heating^c (%)	6.88	(0.25)	7.68	(0.27)	0.80	(0.01)	0.46	2731	768
Electric water heating^d (%)	62.36	(0.48)	61.85	(0.49	0.51	(0.02)	0.80	2731	768

Note: ^{a}Appliances, include dryers, washers, dishwashers, electric cookers, freezers, and water pops top, are coded at 3; ^{b}Electronics, include televisions, computers, laptop, and game consoles, are top coded at 4; ^{c}Electric heating includes central heating, storage heating, and plug-in heaters; ^{d}Electric water heating includes central, immersion, or instantaneous water heater.

Table 2.4: Summary Statistics of Treatment and Control Groups

2.5 The Data

The electricity consumption data, collected in half hour intervals from July 14, 2009 to December 31, 2010, are used extensively in this analysis. I aggregate usage observations to the daily totals for each period. The Commission for Energy Regulation in the Republic of Ireland reports that the average household uses 5,067 kWh of electricity in 2009 [72]. The average daily consumption of the households in the sample ranges from 11.67-12.26 kWh (11.46-12.08 kWh on weekdays) from July to December of 2009 (see Table 2.45), an estimated average of 4,258-4,475 kWh in

2009.

The temperature in Fahrenheit is an average of the average daily temperature from four weather monitoring stations located in four of Ireland's airports: Cork, Dublin, Galway, and Shannon. Since the temperature correlations between the stations are high (correlation coefficients of 0.963-0.980), I average the observations from each station. I use these 24-hour temperature averages to calculate the daily heating degree-day. The year 2009 had average annual heating degree-days (HDD) of 5794.85, and this was slightly warmer than that of 2010, which had an average of 6414.95 heating degree-days. Annual cooling degree-days are 0.625 for 2009 and 0 for 2010[11]. The trial period (July 14, 2009 to December 31, 2010) did not witness average daily temperatures over 65° F. Daylight hours are also available with an annual average of 4486.19 hours of daylight for both years.

2.5.1 Is there self-selection into the sample?

One concern with any analysis is that households voluntarily participated in the study, and therefore estimates may be biased. In theory, random assignment to treatment and control groups should render both groups to have insignificant differences. One possible explanation as to why they are different could be that households with older or less educated residents assigned to the treatment group may have found the treatment difficult to understand or adopt, resulting in their

[11]The milder and rainy weather in Ireland is similar to that of the state of Washington (2009: HDD= 6651.40, CDD=185.59; 2010: HDD=6448.16, CDD=91.38)

withdrawal from the trial.[12]

I estimate a probit model as an indirect way to check for selection into the sample. This is to ensure there are no significant differences between the treatment and control groups. In the model, the dependent variable takes on a value of one if household i is assigned to the treatment group and 0 if otherwise. This variable is then regressed on household and building characteristics with results shown in Table 2.5. A test of joint significance for the explanatory variables rejects the null hypothesis at the 5 percent level[13], $\text{Chi}^2(18)= 34.93$, p=0.010. The t-tests for each coefficient show that there are also a few variables that are significant and this is consistent with Table 2.4 that compares the difference in means between the treatment and control group. I find statistically significant differences in the mean of the variables for baseline usage, number of residents, number of electronics, employment status, age, education level, and type of home.

These baseline differences should be accounted for using fixed effects estimation with individual household fixed effects. Additionally, a Wald test on coarsened exact matching (CEM)[14] estimates in Table 2.5 fails to reject the null hypothesis at

[12] The aging studies literature has often found evidence of a digital divide in that older adults are less likely to be involved in high level use, culture, and pleasures of using information and communication technology [67].

[13] Di Cosmo et al. (2014) perform a similar test on the same data, but found no significance at the 5 percent level. The difference here is that I use a more exhaustive set of explanatory variables in this regression model.

[14] Coarsened exact matching improves the estimation of casual effects by reducing the imbalance in covariates between treatment and control groups by matching observations similar in covariates between the treatment and control group and trimming observations that fail to match [49]. Further

Treatment	All	(S.E.)	CEM	(S.E.)
Average daily usage in 2009	1.99E-04	(0.003)	9.67E-04	(0.003)
No. of residents	-0.001	(0.015)	-0.041**	(0.020)
Age 18-35^D	-0.122	(0.110)	-0.208	(0.145)
Age 36-55^D	-0.113	(0.078)	-0.043	(0.103)
No formal education^D	-0.072	(0.223)	-0.190	(0.328)
Primary education^D	-0.203**	(0.092)	-0.345**	(0.115)
Secondary education^D	-0.028	(0.059)	-0.058	(0.071)
Employed^D	0.288***	(0.080)	0.115	(0.101)
Unemployed^D	0.254**	(0.115)	-0.050	(0.182)
Homeowner^D	0.019	(0.118)	0.059	(0.162)
No. of bedrooms	0.032	(0.040)	0.051	(0.046)
Apartment^D	-0.173	(0.213)	-0.106	(0.331)
Semi-detached house^D	-0.028	(0.087)	0.087	(0.110)
Detached house^D	-0.079	(0.085)	0.083	(0.108)
No. of appliances	-0.006	(0.016)	0.006	(0.019)
No. of electronics	0.024	(0.015)	-0.008	(0.021)
Electric space heating^D	-0.051	(0.102)	0.041	(0.114)
Electric water heating^D	0.020	(0.056)	0.004	(0.065)
Constant	0.394	(0.177)	0.251	(0.263)
Observations	2,589		1,830	

Standard errors in parenthesis. $*p < 0.10, **p < 0.05, ***p < 0.01$

Note: The first probit model includes all households in the treatment and control groups that completed the survey. The second probit model includes household in the treatment and control groups trimmed with coarsened exact matching.

Table 2.5: Probit Results

the 5 percent level (Chi^2(18)= 23.93, p=0.157), suggesting there are no significant differences between the two groups after CEM is applied.

2.6 The Models

The aim of this paper is to estimate the effect of information provision and adaptation on usage throughout the trial. The half hourly usage data is aggregated to the period level per day for each household in the treatment control groups. There are four observations per day representing "before peak" (8am to 4:59pm), "peak" (5pm to 6:59pm), "after peak" (7pm to 10:59pm), and "night" (11pm to 7:59am) period usage. Figure 1a compares the average daily peak usage in the treatment and control groups. While immediate reductions in energy usage are evident from the IHD treatment group, the effects gradually dissipate down to the level similar to billing-only households. This phenomenon suggests that the effectiveness of the IHD wanes over time and blends into the background of a households routine.

I estimate the following model for the combination of three information treatments and four periods of the day:

$$Y_{idmyw} = \alpha_i + \rho_w + \phi_{my} + \gamma S_{dmy} + \sum_{n=1}^{12} \sum_{t \in T} \beta_{n,t}([Month_m]_n \times [TREAT_{iy}]_t) + \epsilon_{idmyw} \tag{2.1}$$

where Y_{idmyw} is the natural log of household is daily electricity usage in kWh for period p of each weekday w, day d in month m of year y. The vector of treatment

emphasis of this method is explained in section 5.1.

dummies, $TREAT_{iy}$, take a value of 0 for the control group and all observations during the benchmark period, and a value of 1 for households in either the IHD, monthly, and bi-monthly information treatment groups after the trial begins. It is interacted with a vector of monthly dummies, indicated by $Month_m$, for each month of the testing period.

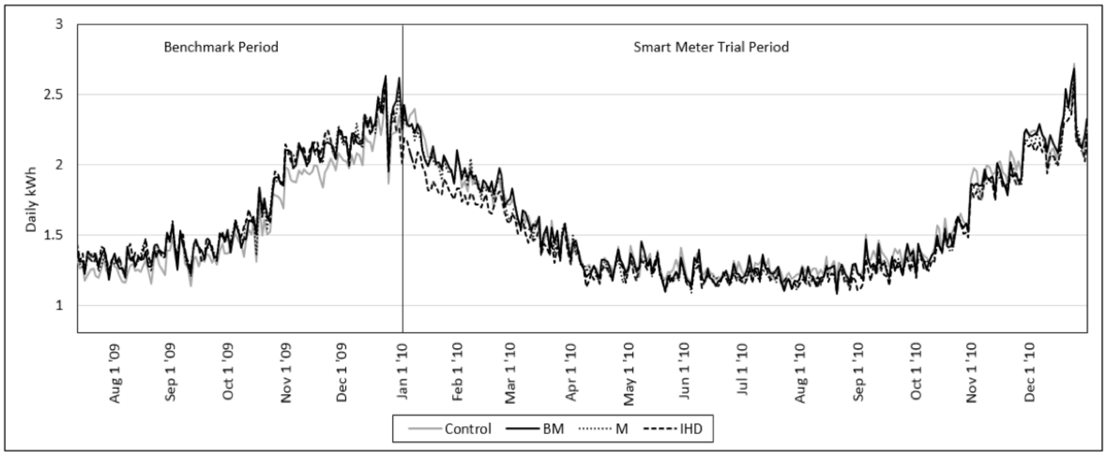
I control for a vector of seasonal variables S_{dmy} including an indicator for a bank holiday, the natural log of heating degree-days and daylight hours. Day of the week fixed effects, denoted by ρ_w, and month by year fixed effects, denoted by ϕ_{my}, control for variations in usage due to changes in the work day and season, respectively. Observations where residents of the household are probably away from home (their daily usage is below 0.1 kWh for 12 consecutive days or more) are dropped from the analysis. Residents that are away for long periods of time may bias estimates if they are not present to react to changes in price. Additionally, I restrict my observations to weekday usage as weekends are on a different tariff schedule and do not have peak periods. I estimate Equation 2.1 separately for each period of the day: day1, peak, day2, and night for a total of 4 regressions.

The coefficients $\beta_{I,n}$ are the average treatment effects by treatment, period, and month of the trial. Standard errors are clustered two ways at the household and day of the trial level as household is errors may be correlated at the household and day level. Finally, ϵ_{idmyw} is an unobserved error term. The fixed effects model is estimated using the within estimation approach, which allows for a more flexible model, exploiting the variation over time within each household. I perform a Hausman test and reject the null hypothesis suggesting effects are correlated with the covariates and that the fixed-effects model is appropriate, $\text{Chi}^2(32) = 1.6\text{e}{+}06$ (p=0.000).

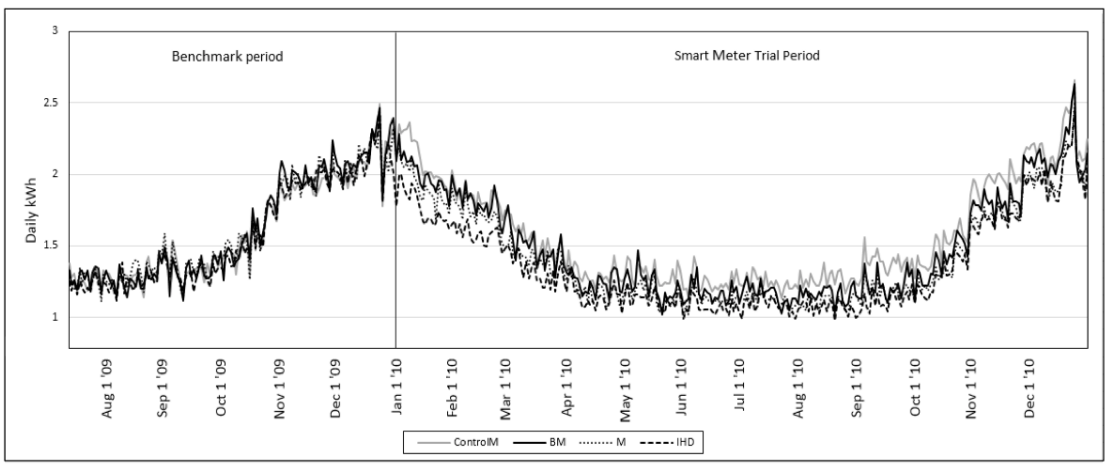
Since the main approach is a difference-in-differences estimation, it must meet the assumption of parallel trends. A pre-treatment trends check between the treatment and control groups to determine whether there are significant differences in trends between the two groups is done for the benchmark period (model not shown). I dont find evidence of different trends between the groups before the treatment period, $F_{169,3419} = 0.99$, p=0.53. I then estimate the following specifications to test for robustness of results. The first estimates Equation 2.1 using hourly observations, doubling the observations for the peak period. The third specification introduces day of the trial fixed effects t, which lends to a more flexible model. This specification is more flexible and excludes the variables *HDD*, *daylight*, and *holiday* since they are controlled for with day of the trial fixed effects.

Finally, I correct for the differences in the control and treatment groups. In Figure 2.2(a), the control group energy consumption remains below the consumption of the treatment groups throughout the benchmark period. While the design of the trial is a randomized control, a participants decision to withdraw from his participation may be correlated to his assigned treatment. One possible explanation is that older or less educated participants may find the TOU structure to be difficult to understand and withdraw from the trial resulting in an overestimation of the effects.

I apply coarsened exact matching (CEM) (see Iacus et al. (2011)) to trim the sample in order to achieve a better balance of the covariates between the treat-



(a) Average daily peak electricity consumption for the treatment and control groups



(b) Average Daily Peak Electricity Consumption for Treatment and Control Groups with Coarsened Exact Matching

Figure 2.2: Average Daily Peak Electricity Consumption for Treatment and Control Groups

ment and control groups. I match households on variables that were found to be significantly different across the control and treatment groups in Section 5.1: age, education, employment status, type of house, number of electronics, and number of residents. The control and treatment households are assigned to one of s strata based on these characteristics. Households in the control group placed in the same stratum as treatment units serve as matched controls for the latter. Weights are assigned to each household. Households in the treatment group are assigned a weight of 1 and households in the control group are assigned a weight of $\frac{m_C}{m_T} \cdot \frac{m_C^s}{m_T^s}$ where m_C and m_T are the number of households in the control and treatment groups, respectively, and m_C^s and m_T^s are the number of matched control and treatment households in strata s, respectively. Unmatched households are assigned a weight of 0. Figure 2.2(b) shows the daily peak electricity consumption with CEM and the baseline consumption of the control and treatment groups to be closely matched prior to January 1, 2010.

I further aim to understand the impact of learning and the effect of information with TOU pricing on overall daily consumption. Carroll et al. (2014) estimates a similar DID fixed effects model to compare reduction in overall usage between pre trial and testing period and finds the largest reductions coming from monthly billing by 2.9 percent. However, household usages are aggregated to a total of two observations per household, one before the trial and one during, and ignore seasonal variation. By contrast, I estimate the daily average treatment effect for each month of the trial using a similar specification to Equation 2.1. Additionally, I estimate a single average treatment effect for the trial and a specification including only observations during the trial with corresponding baseline usage, that is observations from July 14 to December 31 of 2009 and 2010, to identify whether increasing information through reports and IHDs encourages conservation in the form of reduced overall energy usage.

I estimate the following:

$$Y_{idmyw} = \alpha_i + \rho_w + \phi_{my} + \gamma S_{dmy} + \beta_1 BM_{imy} + \beta_2 M_{imy} + \beta_3 IHD_{imy} + \epsilon_{idmyw} \quad (2.2)$$

where BM_{imy}, M_{imy}, IHD_{imy} take a value of 1 for households in a bi-monthly, monthly, or IHD treatment group, respectively, during the testing period and 0 otherwise. In this case, the betas are the daily average treatment effects for information treatments. Observations are aggregated at the daily level and standard errors are clustered at the household level. I repeat this analysis with a sample that applies CEM with weights as a robustness check.

2.7 Results and Analysis

Table 2.6 presents the estimates of Equation (1) for the peak, day1, day2, and night periods from using the full sample period from July 14, 2009 to December 31, 2010. Within the table are three Columns for the bi-monthly bill and energy report (BM), monthly bill and energy report (M), and IHDs with a bi-monthly bill and energy report (IHD). Separate regressions are run for each information treatment and compared to the control for the four periods of the day.

	Day1(8am-4:59pm)		Peak (5pm-6:59pm)		Day2 (7pm-10:59pm)		Night (11pm-7:59am)	
	(1)		(2)		(3)		(4)	
Bi-monthly Billing								
January	-0.018	(0.011)	-0.039***	(0.009)	-0.005	(0.010)	0.012	(0.011)
February	-0.004	(0.011)	-0.022***	(0.008)	0.009	(0.010)	0.014	(0.010)
March	0.014	(0.010)	-0.030***	(0.008)	0.009	(0.009)	0.025***	(0.009)
April	0.006	(0.010)	-0.036***	(0.008)	-0.004	(0.009)	0.022***	(0.008)
May	-0.014	(0.010)	-0.046***	(0.008)	-0.008	(0.009)	0.013	(0.008)
June	-0.006	(0.011)	-0.043***	(0.008)	-0.008	(0.010)	0.017**	(0.009)
July	-0.017	(0.012)	-0.043***	(0.009)	-0.016	(0.010)	0.018*	(0.009)
August	-0.023**	(0.012)	-0.047***	(0.009)	-0.017*	(0.010)	0.018*	(0.009)
September	-0.015	(0.011)	-0.048***	(0.009)	-0.009	(0.010)	0.020**	(0.009)
October	-0.017	(0.011)	-0.044***	(0.009)	-0.004	(0.010)	0.020**	(0.009)
November	-0.009	(0.012)	-0.046***	(0.010)	-0.012	(0.010)	0.025**	(0.011)
December	-0.003	(0.015)	-0.023**	(0.010)	-0.003	(0.012)	0.018	(0.014)
Monthly Billing								
January	-0.027**	(0.011)	-0.045***	(0.009)	-0.014	(0.010)	-0.013	(0.011)
February	-0.019	(0.012)	-0.031***	(0.009)	0.003	(0.010)	0.002	(0.010)
March	-0.003	(0.011)	-0.037***	(0.008)	0.001	(0.009)	0.011	(0.009)
April	-0.022**	(0.010)	-0.045***	(0.008)	-0.013	(0.009)	0.008	(0.008)
May	-0.024**	(0.010)	-0.048***	(0.008)	-0.009	(0.009)	0.010	(0.008)
June	-0.017	(0.011)	-0.047***	(0.008)	-0.007	(0.010)	0.013	(0.009)
July	-0.024**	(0.012)	-0.054***	(0.009)	-0.015	(0.010)	0.018*	(0.010)
August	-0.030***	(0.011)	-0.054***	(0.009)	-0.019*	(0.010)	0.013	(0.009)
September	-0.027**	(0.012)	-0.056***	(0.008)	-0.007	(0.010)	0.016*	(0.010)
October	-0.035***	(0.011)	-0.052***	(0.009)	-0.009	(0.010)	0.013	(0.009)
November	-0.026**	(0.012)	-0.054***	(0.009)	-0.010	(0.010)	0.016	(0.011)
December	-0.025*	(0.014)	-0.043***	(0.010)	-0.011	(0.012)	-0.011	(0.014)
IHD + Bi-monthly Billing								
January	-0.053***	(0.011)	-0.093***	(0.009)	-0.045***	(0.010)	-0.011	(0.011)
February	-0.038***	(0.012)	-0.071***	(0.009)	-0.026***	(0.009)	0.004	(0.010)
March	-0.020*	(0.010)	-0.058***	(0.008)	-0.014	(0.009)	0.008	(0.009)
April	-0.016*	(0.009)	-0.049***	(0.008)	-0.015*	(0.008)	0.014*	(0.008)
May	-0.025***	(0.010)	-0.053***	(0.008)	-0.013	(0.009)	0.019**	(0.008)
June	-0.015	(0.011)	-0.053***	(0.008)	-0.014	(0.010)	0.017**	(0.009)
July	-0.014	(0.011)	-0.051***	(0.009)	-0.010	(0.010)	0.015	(0.009)
August	-0.016	(0.011)	-0.060***	(0.009)	-0.010	(0.009)	0.022**	(0.009)
September	-0.017*	(0.010)	-0.070***	(0.008)	-0.010	(0.009)	0.020**	(0.009)
October	-0.012	(0.011)	-0.053***	(0.008)	-0.000	(0.009)	0.025***	(0.009)
November	-0.017	(0.012)	-0.064***	(0.010)	-0.012	(0.010)	0.023**	(0.010)
December	-0.026*	(0.014)	-0.055***	(0.010)	-0.022*	(0.011)	-0.002	(0.014)
Weekday fixed	yes		yes		yes		yes	
Month×year	yes		yes		yes		yes	
Heating degree days	S(+)		S(+)		S(+)		S(+)	
Holiday	S(+)		NS		S(-)		NS	
Daylight hours	S(-)		S(-)		S(-)		S(-)	
Households	3,334		3,334		3,334		3,334	
Observations	1,278,568		1,278,568		1,278,568		1,278,568	

Standard errors in parenthesis. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table 2.6: Average Monthly Information Treatment Effects by Period of the Day

2.7.1 Peak hours

The daily average treatment effects of the TOU pricing and information treatment during the peak periods for each month of the year are reported in Table 2.6, Columns 4-6. Households on TOU pricing and receiving a bi-monthly bill reduce their peak usage by 2.22 and 4.92 percent per day. More frequent arrival of bills (with monthly frequency) indicates an average reduction of 3.05 and 5.45 percent in kilowatt-hours per day. IHD households reduce their daily consumption on average by 4.78 and 8.88 percent. These effects are significant for all information treatments.

From these results, it would seem that the households provided with more information about their consumption attain proportionally larger reductions in consumption. Energy bills and reports may act as reminders for households to be more aware of their usage and conserve energy. The more frequent the arrival of bills and reports, the more often is a household's usage brought to their attention. With bi-monthly bills, there is a longer period in between the arrival of bills and households slide back into their old habits as their efforts to reduce usage decline. This finding is consistent with the study by Allcott and Rogers (2014) who finds attenuation in the reduction of energy usage directly following a conservation report as more reports are delivered.

Households receiving bi-monthly and monthly bills show a steadily increasing reduction of peak usage throughout the trial. The average treatment effect for households with IHDs starts out with the highest reduction of 8.88 percent but gradually declines to effects close to that of the households under monthly billing

	(1)		(2)		(3)	
	$H_0 : \beta_M = \beta_{BM}$		$H_0 : \beta_{IHD} = \beta_{BM}$		$H_0 : \beta_{IHD} = \beta_M$	
	$F_{1,3333}$	Prob>F	$F_{1,3333}$	Prob>F	$F_{1,3333}$	Prob>F
January	0.44	0.5078	36.57	**0.0000**	29.89	**0.0000**
February	1.00	0.3173	29.49	**0.0000**	17.08	**0.0000**
March	0.79	0.3746	11.36	**0.0008**	6.27	**0.0123**
April	1.13	0.2870	2.77	0.0958	0.21	0.6477
May	0.10	0.7549	0.69	0.4062	0.30	0.5808
June	0.25	0.6200	1.25	0.2641	0.38	0.5371
July	1.48	0.2245	0.76	0.3823	0.12	0.7336
August	0.53	0.4654	1.96	0.1620	0.46	0.4963
September	0.73	0.3944	5.50	**0.0190**	2.27	0.1315
October	0.80	0.3708	1.19	0.2763	0.04	0.8453
November	0.67	0.4141	3.30	0.0691	1.04	0.3089
December	3.41	0.0647	9.09	**0.0026**	1.36	0.2439

Note: Joint F test for significant difference between information treatment effects for individual months of the year for $H_0 : \hat{\beta}_M = \hat{\beta}_{BM}, H_0 : \hat{\beta}_{IHD} = \hat{\beta}_{BM}$, and $H_0 : \hat{\beta}_{IHD} = \hat{\beta}_M$, respectively. Column 1 compares monthly and bi-monthly treatment effects, Column 2 compares IHD with bi-monthly treatment effects, and Column 3 compares IHD and monthly treatment effects. Significant differences at the 5% level indicated in bold.

Table 2.7: Peak Period Information Treatment Joint F Tests of Significance

within three months. This suggests that IHDs enable faster learning but the initial advantage of real time information dissipates as households reach a steady state. After that point, monthly bills are as effective as IHDs. The finding that IHDs become less effective in reducing energy usage over time is consistent with Hargreaves et al. (2013) who suggest that IHDs gradually become "backgrounded," that is, blended into the background of household routines.

Table 2.7 shows results from comparison of treatments from Equation 2.1. Column 1 shows that increasing the frequency of bills from bi-monthly to the monthly level does not significantly influence the peak consumption. A test of joint significance for the monthly treatment coefficients fails to reject the null hypothesis at the 5 percent level ($F_{12,3419} = 0.54$, p=0.8884). On the other hand, IHD access decreases usage during peak hours by 2.08 to 4.69 percent more than households receiving monthly billing and 2.76 to 5.26 percent more than bi-monthly billing. The IHD and month effects become insignificantly different from one another after the third month of the trial. This further suggests that improving real time information is most effective in the early months of the trial.

2.7.2 Non-peak hours

Table 2.6, Columns 1 and 3 show effects of information on usage for hours before peak (from 8am to 5pm) and after peak (from 7pm to 11pm), respectively. The periods are treated as separate periods to account for differences in household behaviors during times of daylight and evening. Bi-monthly billing does not have any significant effects on usage during either time period. Monthly billing maintains consistent and significant reductions on average by 2.18 to 3.44 percent before peak and insignificant reductions post peak. This can be due to households waiting until after the peak period to run their appliances or turning on lights, making it less likely to have reductions in consumption. In Column 1, IHDs suggest significant reductions in usage within the first five months of the trial but at a decreasing rate from 5.16 down to 1.59 percent. The IHD group reduces its consumption during this period more than the bi-monthly group by 2.19 to 3.38 percent during the first four months. In Column 3, the post peak period IHD group reveal significant differences between 2.18 and 3.92 percent more in reductions than the bi-monthly group for the first three months.

Estimates for nighttime hours (between 11pm and 7:59am) are reported in Table 2.6 Column 4. In contrast with the average treatment effects during day times, average treatment effects for bi-monthly billing show an increase in usage from a weakly significant 1.69 percent to a significant 2.47 percent in March and remains consistent throughout the year. Estimates for monthly households are insignificant. Households with IHDs show a similar pattern as households on monthly billing by starting out with reductions in the first month before showing significant increasing usage effects in the fourth month. The increase in usage varies between 1.41 and 2.53 percent. This shift in electricity usage from peak and day periods to the night period implies households wait until after 11pm or before 8am to run major appliances. The effects of the treatments are not significantly different from one another after the first month for all information treatments.

2.7.3 Alternative specifications

Table 2.8 includes alternative specifications to Equation 2.1 estimated for the peak period. I utilize data at a higher resolution (i.e. hourly) to estimate treatment effects. Column 1 reveals similar usage patterns and significant hourly decrease of 3.54 to 6.48 percent. Estimates are smaller in magnitude since average treatment effects reductions are estimated by hour for each period compared to previous estimates for reduction per period. Despite introducing 535 fixed effects the estimates remain robust for each treatment across the four periods.

	FE, hourly (1)		FE, DOT (2)		FE, CEM (3)	
Bi-monthly Billing						
January	-0.029***	(0.007)	-0.039***	(0.009)	-0.036***	(0.013)
February	-0.015***	(0.006)	-0.022***	(0.008)	-0.029***	(0.011)
March	-0.021***	(0.005)	-0.030***	(0.008)	-0.023**	(0.011)
April	-0.027***	(0.005)	-0.036***	(0.008)	-0.024*	(0.012)
May	-0.032***	(0.006)	-0.046***	(0.008)	-0.036***	(0.011)
June	-0.031***	(0.006)	-0.043***	(0.008)	-0.035***	(0.012)
July	-0.029***	(0.006)	-0.043***	(0.009)	-0.048***	(0.012)
August	-0.033***	(0.006)	-0.047***	(0.009)	-0.048***	(0.013)
September	-0.034***	(0.006)	-0.048***	(0.009)	-0.059***	(0.012)
October	-0.032***	(0.006)	-0.044***	(0.009)	-0.041***	(0.012)
November	-0.033***	(0.007)	-0.046***	(0.010)	-0.047***	(0.013)
December	-0.017**	(0.008)	-0.023**	(0.010)	-0.026*	(0.015)
Monthly Billing						
January	-0.034***	(0.007)	-0.045***	(0.009)	-0.052***	(0.013)
February	-0.022***	(0.006)	-0.031***	(0.009)	-0.039***	(0.012)
March	-0.027***	(0.006)	-0.037***	(0.008)	-0.037***	(0.011)
April	-0.032***	(0.005)	-0.045***	(0.008)	-0.049***	(0.012)
May	-0.034***	(0.005)	-0.048***	(0.008)	-0.052***	(0.011)
June	-0.033***	(0.005)	-0.047***	(0.008)	-0.056***	(0.011)
July	-0.038***	(0.006)	-0.054***	(0.009)	-0.057***	(0.012)
August	-0.038***	(0.006)	-0.054***	(0.009)	-0.066***	(0.013)
September	-0.039***	(0.006)	-0.056***	(0.008)	-0.069***	(0.012)
October	-0.037***	(0.006)	-0.052***	(0.009)	-0.057***	(0.012)
November	-0.039***	(0.007)	-0.054***	(0.009)	-0.057***	(0.013)
December	-0.032***	(0.007)	-0.043***	(0.010)	-0.061***	(0.015)
IHD + Bi-monthly Billing						
January	-0.067***	(0.007)	-0.093***	(0.009)	-0.089***	(0.012)
February	-0.050***	(0.006)	-0.071***	(0.009)	-0.078***	(0.012)
March	-0.042***	(0.006)	-0.058***	(0.008)	-0.057***	(0.011)
April	-0.036***	(0.005)	-0.049***	(0.008)	-0.045***	(0.012)
May	-0.038***	(0.006)	-0.053***	(0.008)	-0.050***	(0.010)
June	-0.038***	(0.006)	-0.053***	(0.008)	-0.052***	(0.011)
July	-0.036***	(0.006)	-0.051***	(0.009)	-0.042***	(0.012)
August	-0.042***	(0.006)	-0.060***	(0.009)	-0.055***	(0.012)
September	-0.049***	(0.006)	-0.070***	(0.008)	-0.081***	(0.011)
October	-0.040***	(0.006)	-0.053***	(0.008)	-0.054***	(0.011)
November	-0.046***	(0.007)	-0.064***	(0.010)	-0.073***	(0.013)
December	-0.040***	(0.008)	-0.055***	(0.010)	-0.060***	(0.015)
Weekday fixed	yes		yes		yes	
Month×year	yes		yes		yes	
Heating degree	S(+)		no		S(+)	
Holiday	NS		no		S(-)	
Daylight Hours	S(-)		no		S(-)	
Households	3,334		3,334		1,884	
Observations	2,470,546		1,278,568		723,255	

Standard errors in parenthesis. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table 2.8: Robustness Estimation of Average Treatment Effects for Peak Consumption

Table 2.8 Column 2 shows estimates with day of the trial fixed effects t. Despite introducing 535 additional controls, the estimates remain robust for each treatment across the four periods. Substituting daily seasonal controls with daily fixed effects yields similar results of 4.78 to 8.88 percent in peak reductions. Column 3 models estimated with CEM data show IHD effects to range from 4.01 to 8.52 percent during the peak period, similar to that of the original specification. Similar to findings for Equation 2.1, effects begin to dissipate after the first month and match the reductions of the monthly billing group after March. The new estimates show peak effects to have larger magnitudes in a majority of the estimates for monthly and IHD group and bi-monthly effects for the last four months of the year.

2.7.4 Daily Level Average Treatment Effects

Results in Table 2.9 show how the provision of information in conjugation with a price policy such as TOU pricing encourages households to reduce their average weekday usage. Households respond differently to TOU pricing depending on the frequency of billing and reports. Providing reports with bi-monthly bills does not affect usage during any month in the trial. Monthly billing shows significant reductions in overall usage during 6 nonconsecutive months of the trial up to 2.86 percent in Column 2, and 3.63 percent for CEM adjusted estimates during the latter half of the trial in Column 5. The largest reductions come from the early months of the trial for households with IHD at 6.20 percent in January but which disappear

	FE (1)		FE,CEM (2)	
Bi-monthly Billing				
Jan-Mar	-0.001	(0.010)	0.008	(0.014)
Apr-Jun	-0.004	(0.009)	0.014	(0.013)
Jul-Sep	-0.014	(0.010)	-0.013	(0.014)
Oct-Dec	-0.009	(0.011)	-0.009	(0.016)
Monthly Billing				
Jan-Mar	-0.016	(0.010)	-0.018	(0.014)
Apr-Jun	-0.016*	(0.009)	-0.019	(0.013)
Jul-Sep	-0.020*	(0.011)	-0.033**	(0.015)
Oct-Dec	-0.025**	(0.011)	-0.039**	(0.016)
IHD + Bi-monthly Billing				
Jan-Mar	-0.042***	(0.010)	-0.042***	(0.013)
Apr-Jun	-0.014	(0.009)	-0.017	(0.013)
Jul-Sep	-0.013	(0.010)	-0.023	(0.014)
Oct-Dec	-0.019*	(0.011)	-0.020	(0.015)
Weekday fixed effects	yes		yes	
Month×year fixed effects	yes		yes	
Heating degree days	S(+)		S(+)	
Holiday	S(+)		S(+)	
Daylight hours	S(-)		S(-)	
Households	3,334		1,884	
Observations	1,278,568		722,671	

Standard errors in parenthesis. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table 2.9: Monthly Average Treatment Effects for Weekday Consumption

	Full Sample		July 14 - December 31	
	(1a) FE	(1b) FE, CEM	(2a) FE	(2b) FE, CEM
Bi-monthly Billing	-0.007	-0.000	-0.013	-0.012
	(0.008)	(0.011)	(0.009)	(0.012)
Monthly Billing	-0.019***	-0.027**	-0.023**	-0.037***
	(0.007)	(0.011)	(0.009)	(0.014)
IHD + Bi-monthly Billing	-0.022***	-0.025**	-0.017**	-0.023*
	(0.007)	(0.010)	(0.009)	(0.012)
Weekday fixed effects	yes	yes	yes	yes
Month×year fixed effects	yes	yes	yes	yes
Heating degree days	S(+)	S(+)	S(+)	S(+)
Holiday	S(+)	S(+)	S(+)	S(+)
Daylight hours	S(-)	S(-)	S(-)	S(-)
Households	3,334	1,884	3,334	1,884
Observations	1,278,568	722,671	818,872	465,905

Standard errors in parenthesis. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table 2.10: Average Treatment Effects for Weekday Consumption

after March. The CEM approach shows a slightly lower estimate for January of 5.26 percent. Estimates in Column 6 tend to be higher in magnitude and more significant than their counterparts in Column 3. Providing a household with real time information appears to have a larger effect on the overall daily consumption although much of the reduction came from the beginning of the trial. Much of the reduction disappears after the arrival of the first bill in March.

While the main purpose of a TOU pricing is to encourage households to shift consumption away from peak times and alleviate grid congestion during peak hours, improving information provision appears to attain reductions in overall consumption. Table 2.10 Columns 1a and 1b show an overall reduction of 1.88 percent for monthly billing and a 2.18 percent reduction after CEM adjustment, respectively.

	Savings for year 1 (kWh/year)	Savings for years 2-10 (kWh/year)	10 year savings (kWh)	Additional treatment cost per year	Cost per kWh
IHD*	67.13	52.01	535.19	€2.30-6.15	€0.043-0.0115
M**	58.07	70.15	689.43	€4.38-6.42	€0.064-0.093
BM	0	0	0	€0	€0

Notes: *Cost of device estimated between €23.04-61.48 [27]. **Ireland domestic mail costs approximately €0.48-0.57 cents per unit for bulk mailers (Postal rates based on bulk mailer rates from www.anpost.ie). Assuming each bill has printing cost (paper, ink, data processing, etc.) of €0.25-0.50 for 6 bills per year additional to the bi-monthly bills. The minimum additional cost to monthly billing will be (€0.48 + €0.25)×6 months = €4.38 per year. Estimates converted to 2014 values for comparison.

Table 2.11: Information Treatment Cost Comparison

IHD treatment has larger reductions of 2.27 percent and 2.47 percent, respectively. Estimates for overall weekend consumption were found to be insignificant (not shown here). Columns 2a and 2b show estimates for the testing period restricted to the second half of the trial from July 14 through December 31. For monthly billing, I find a reduction of 2.27 percent, consistent with estimates reported by the Commission of Energy Regulation [20], and a 3.63 percent reduction after CEM adjustment. In comparison, I find a 1.69 percent reduction and 2.27 percent after CEM adjustment for the IHD treatment. Estimates for Bi-monthly billing are insignificant. While estimates comparing monthly billing and IHD show differing results under full sample and restricted sample analysis, t-tests reveal monthly billing and IHD estimates are not significantly different from one another for all four models.

2.7.5 Cost Comparison

I use the empirical results in Table 2.10 to estimate weekday savings for the average treatment effects in a back of the envelope calculation. I assume that estimates from Table 11 Column 1a reflect savings from the first year of the intervention and Column 2a for the years following, as the initial large impact from the start of the trial would have dissipated. I find that over a 10 year period, information treatments would result in weekday savings of 535.19 kWh (equivalent to powering a 60 Watt light bulb for 371.66 days) for IHD households, 689.43 kWh for monthly billing (equivalent to powering a 60 Watt bulb for 478.77 days), and 0 kWh for bi-monthly billing (see Table 2.11).[15]

Assuming an IHD costs between €23 and €60 with a life expectancy of 10 years [27], the cost per kWh saved is €0.043-0.115. In comparison with monthly billing over 10 years, the cost for printing and delivery, assumed to fall between €43.80 and €64.20, will result in cost per kWh saved to be €0.064-0.093. Based on these assumptions, the cost of a monitor will have to be less than €34.25 in order to be more cost effective than monthly billing. Both estimates induce cost effective energy savings as they are both less than the flat rate tariff per kWh of electricity prior to the start of the trial (14.1 cents/ kWh). However, monthly billing may generate more cost savings than an IHD.

[15] Estimates based on weekday average consumption of 11.821 kWh and 261 weekdays in a year, respectively.

2.8 Conclusion

The aim of this study was to estimate the effects of information provision in conjunction with a TOU pricing scheme that motivates consumers to shift or reduce their consumption from peak to off peak periods of the day. It is important to note that the results in this paper are specific to a single experiment and may not be applicable in other situations. Past studies have argued that information alone is not enough to encourage change in behavior and adoption of conservation practices. Households need additional incentives to encourage participation. At the same time, the effectiveness of pricing policies applied to reflect the real price of electricity might be dampened due to imperfect information on the consumer side. Information on usage and energy prices will allow households to make more informed and more efficient decisions on their energy consumption during various times of the day.

Previous studies have analyzed the effects of information with pricing policies but none have yet compared the billing frequency with information technology with a policy designed to curtail usage during specific times. This paper studies the combination of information with pricing to analyze how households adapt to different types of information provision over time. Findings suggest that at the beginning of the testing period there is a period of learning from households with IHDs where large reductions in usage are made. These gains in conservation quickly diminish after the third month, around the time of the arrival of the first bill. After this learning period, IHDs continue to reduce consumption during the peak period but at levels similar to households on monthly and bi-monthly billing. This suggests that households have learned all they can from the IHD and the display has blended into the background of household routines. On the contrary, adaptation to the treatment during peak times for the monthly and bi-monthly treatment groups are at a gradual increase throughout the trial.

From a conservation perspective, IHDs appear to have a larger impact on reducing overall energy usage but most of these gains come from the beginning of the trial. When analyzing effects from the latter half of the trial, households on monthly billing are able to reduce their overall consumption more than IHD households. While real time information is effective in reducing initial consumption, it may be less effective in encouraging conservation practices than conventional billing methods in the long run. It should be noted that seasonality could play a factor in the responsiveness associated with IHDs in the early months of the trial, which also happen to be the coldest months of the year. However this is not a huge concern due to the low proportion of households that rely on electricity as their main fuel for space heating and the monthly fixed effects.

One suggestion to maintain the strength of the effects is to increase the frequency of bills for households with IHDs. Households are reminded more frequently through the "shock" of receiving their bill to reduce their consumption. Additionally, to prevent IHDs from falling into the household routines, utilities can change TOU rates on a quarterly basis allowing households to adjust their consumption and a more flexible pricing structure to reflect the cost of electricity generation and demand for different seasons. In practice, some utilities have adopted programs to loan IHDs to residential to allow households to learn about their consumption.[16]

Overall, the provision of information with TOU pricing has strong initial effects but similar to the suggestions of Torriti (2012), IHD may not be as effective with TOU pricing as it is in cases where the price of electricity changes more frequently such as with dynamic pricing. However, there are different drawbacks from applying TOU versus dynamic pricing as TOU pricing allows for the change and adaptation of habits and routines whereas critical peak pricing are infrequent events and real time pricing introduces uncertainty in price. The results are specific to TOU pricing, which has a routine to it, and may not be applicable to dynamic pricing, which does not have a routine, and where real time information may well play a vital role that persists over time. More research will be needed to determine the benefits drawn from IHDs versus billing frequency with different pricing schemes.

[16] San Diego Gas and Electric is an example of a utility that loans IHDs to their customers for a 1-month period.

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Chapter 3: Time-Of-Use Pricing and Heterogeneity in Consumer Response

3.1 Introduction

Growing concerns over environmental quality and climate change have heightened policymakers efforts to increase energy savings through energy efficiency and demand management programs. While these programs were once popular in the 1970s and 80s, they have become increasingly important as of late among those that wish to reduce energy demand, shift peak load, lower energy bills, and/or curtail the generation of greenhouse gas emissions [4, 6]).

In recent years, many countries have called for more transparency in suppliers practices and policies in order to encourage active participation of consumers in the energy market [20]. In 2009, the European Union passed multiple directives, which called for its members to implement the widespread installation of "Smart Metering Systems" that allow utilities to monitor, track, and inform customers of usage information. These polices, Directive 2009/72/EC and Directive 2009/73/EC, reflect the growing effort of demand side management to encourage active participation of consumers and energy efficiency [20, 26].

Overall, these efficiency and demand management programs provide alternatives to the energy suppliers that would otherwise have to increase their generation and transmission capacities, via capital and time intensive ventures. One such alternative scheme available to utilities is time-of-use (TOU) pricing, which encourages load shifting to the other times of the day. During hours of peak demand, suppliers must purchase higher cost electricity from the wholesale market in order to meet the electricity demands. Because of network constraints due to limited generation and grid capacity, generation and transmission congestion can occur during peak hours and prevent the delivery of lowest cost electricity to consumers. Congestion conditions can also reduce the reliability of the grid and make areas more susceptible to outages with costly impacts [3].[1] In addition to more expensive electricity and reduced reliability, transmission congestion also results in inefficiency when electricity is lost through the lines in the form of heat.

The ability for smart meters to record and transmit electricity usage information in real time has allowed utilities to offer TOU and other pricing plans to their customers that encourage load shifting or curtailing demand at specific times. These plans allow the energy price to vary throughout the day and more accurately reflect demand and changes in the costs of production [20, 30]. By charging higher prices during times of peak demand, consumers are encouraged by price signals to shift their usage to less expensive off peak periods in exchange for lower bills.

[1] For example, the California electricity crisis in 2000-2001 caused rolling blackouts through the state due to shortages in electricity supply from market manipulations which resulted in $40 billion of added energy costs, not including costs from black outs and reductions in economic growth [76].

The goal of this paper is to study the impact of TOU pricing in a region that had previously not experienced this type of pricing plan. Concerns exist about the short duration of typical TOU studies, such as [7,11,58], and are expressed by Sexton et al. (1987), who question the ability of the trials to accurately reflect consumer response to TOU pricing. Previous TOU studies consisting of two periods [12, 58], with the peak period spanning from 12 to 16 hours raises concerns about the ability to appropriately capture load-shifting effects away from hours of peak demand when the system is at its peak [57]. To overcome this and other concerns, I examine data form a trial where the treatment period spans from January through December 2010 and the TOU day is divided into three different TOU pricing periods reflect daily demand with the peak period spanning two hours. This trial was conducted in the Republic of Ireland.

In addition to analyzing the effects of TOU pricing on different hours of the day, I examine the heterogeneity in the TOU effects to identify the characteristics of households most responsive to TOU pricing. Determining these characteristics has policy implications for targeting customer groups to optimize load-shifting efforts. Finally, I assess the total impact of TOU pricing to determine whether there exists evidence of overall savings in energy usage and bills paid.

The Irish trial was studied by Di Cosmo et al. (2014) who used random effects models for each period of the day to estimate the impact of TOU pricing and information stimuli on usage. However, such a model imposes strong assumptions on the nature of the unobserved heterogeneity and its correlation with observables. I use a fixed effects model and check carefully for significant differences between the control and treatment group, which is critical for unbiased difference-in-difference estimation. I do not distinguish the different information treatments, which are examined in a separate paper in the previous chapter.

Since I estimate regressions for hourly weekday and weekend usage to analyze the effects of the treatment, I find that reductions in peak usage during the weekdays carry over to the weekends even when peak pricing is not in place. I also find that the effect of the TOU pricing scheme vary with the initial level of usage: the lowest quintile shows evidence of increasing overall usage, whereas households in the upper quintiles show the greatest reduction in their overall usage. A simple calculation and comparison of usage and bills shows, on average, households may be able to increase their overall usage all the while reducing their monthly bill, similar to the main findings in [73].

The rest of this paper is organized as follows: Section 2 reviews the literature, section 3 gives a brief overview of the trial, section 4 describes the models, and section 5 the data. Section 6 presents the estimation results and section 7 concludes.

3.2 Relevant Literature

In recent years, a number of papers have studied consumer response to extreme price jump such as the impact of critical peak pricing (CPP) on residential consumption [51, 53, 78]. CPP differs from TOU pricing in that the former is occasional, whereas TOU exists as a stable recurring plan where the price of electricity is high during peak hours and low during off peak hours. In principle, this allows customers to adjust their habits of consumption according to price changes during fixed periods throughout the day.

Historically, TOU studies undertaken in the 1980s focused primarily on estimating own and cross price elasticities using monthly aggregate consumption during peak and off peak periods [19, 44, 55].

Baladi et al. (1998) compare usage patterns of a flat rate tariff with the tariff of a voluntary TOU program and estimate demand response using the conditional demand system model in Caves et al. (1984). Their results indicate 4.7 percentage point reduction in share of peak usage under the TOU rate in the first stage. The tariff structure in the experiment only consists of a peak (noon-7pm) and off peak period (rest of the day) and did not offer pricing levels at varying degrees. Thus a single elasticity of substitution between peak and off-peak electricity consumption can be estimated. Their main finding is that households under volunteer TOU do not experience significantly larger effects than households on a mandatory TOU scheme.

Filippini (1995a) estimated elasticities for TOU pricing using city level data in Switzerland by deriving the indirect utility function and finds static short- (long-) run elasticities to be -0.6 (-0.71) during peak hours and -0.71 (-1.92) during off peak hours. Filippini (1995b) uses the same data to estimate partial elasticities using an almost ideal demand system model.

More recently, Filippini (2011) argues that the previous studies estimated short run elasticities that do not allow customers to react to changes in price and do not account for investments in energy efficient appliances and retrofits. In his study, he estimates own price elasticities using a dynamic partial adjustment approach and aggregate consumption data from 22 cities in Switzerland that range from 2000 to 2006. Short- (long-) run own price elasticities to range from -0.77 (-1.60) to -0.84 (-2.26) during the peak period and -0.65 (-1.27) to -0.75 (-1.65) during the off peak period. These estimates are very similar to his findings in Filippini (1995a). One limitation of the study is that the data are aggregated at the municipal city level, that there are few cities (22) and the length of the longitudinal component is short.

Researchers have been attempting to model how variable pricing affects residential demand for electricity for some time. While general consensus is that TOU and real time pricing are effective in load shifting, the findings on overall conservation are mixed. Sexton et al. (1989) analyzes the effects of providing households with monitors displaying their usage information in a TOU experiment. They estimate a maximum likelihood model using the weekday ratio of peak and off peak usage. Despite finding evidence of load shifting, they do not find evidence of overall conservation. Allcott (2011), on the other hand, finds evidence of households conserving energy usage during peak hours and did not shift consumption over to off-peak hours in a real time pricing experiment. Matsukawa (2001) investigates the impact of TOU pricing using cross-sectional data on electricity consumption and household survey on Japanese households. Evidence of load shifting is small compared to the incentives, which he attributes to the 16 peak periods.

Other studies have compared the before and after effects of TOU pricing on residential household consumption. Torriti (2012) compares the time-related electricity consumption before (July 1, 2009 - June 30, 2010) and after (July 1, 2010 - June 30, 2011) the introduction of TOU tariffs in Northern Italy and finds that consumption of electricity increased by 13.69 percent but bills decreased by 2.21 percent. Additionally, there is evidence of peak usage shifting to the hour prior to the start of the peak pricing period in the morning and after the end of the peak pricing period in the evening. While these results indicate changes in habits such as waiting to start appliances after a peak period, Torriti notes of a third peak emerging in the middle of the peak pricing period which goes against expectations of shifting consumption away from higher priced periods. Similarly, Bartusch et al. (2011) conduct a before and after demand response analysis of TOU pricing study implemented in Sweden. They find evidence of load shifting by 0.8 percentage points and an overall decline in usage by 11.1 percent over the first year.

3.3 Trial Design

In this paper I use the data from the Irish TOU trial. The Republic of Irelands Commission of Energy Regulation (CER) conducted the Irish Consumer Behavior Trial as part of the National Smart Metering Plan. The trial took place in 2008-2011 to investigate the impact of smart metering technology combined with TOU tariffs and feedback stimuli on consumer behavior on reductions in peak demand and overall electricity use [20].

There are four phases to the trial. A timeline and description of the trial are shown in Figure 2.1. The Pre-Benchmark period occurred from March 2008 through June 2009. During this period participant recruitment took place in four waves. Each wave was adjusted to ensure that the sample was representative of the national population. Smart meters are also installed in participating homes.

From July through December of 2009, the Benchmark period gathered baseline data prior to the start of the test period. During this time, customers are on a bi-monthly billing schedule and the pre-trial survey is conducted. Participants are also randomly assigned to control and treatment groups. Additionally, to ensure households did not pay more than they normally would were they on the regular tariff schedule, households were given the first half of a balancing credit. During the Testing period from January through December 2010, the control group continues to be billed at their existing flat rate at 14.1 cents per kWh on bi-monthly billing whereas the treatment groups face different TOU tariffs and feedback stimuli. The trial ends January 1, 2011 and all participants return to their normal billing cycle and flat rate tariffs. A survey is conducted during this Post-Trial period via telephone and the treatment group receives the second half of their balancing credit.

Although the original 5,375 participants were self-selected into the trial, the assignment of treatment and control were randomized. Records were deleted from the study for participants who withdrew from the trial. A group of households were selected for a special Weekend tariff group on a different tariff structure than the residential treatment group, which is subsequently dropped from this study. Of the original sample, 2,406 remain in the Residential TOU treatment group and 928 in the control group.

Participants in the Residential group are assigned two treatments. The first is the TOU tariff that introduces variation in price throughout the day where each household is assigned to one of four TOU pricing structures shown in Table 2.1. A weekday for the treatment group is divided into four periods where the price of electricity reflects the demand of electricity for those periods. The night period spans from 11pm to 7:59am is the lowest cost period, followed by the day period from 8am to 4:59pm and 7pm to 10:59pm, while the peak period, from 5pm to 6:59pm, has the highest tariff. Weekend days and public holidays exclude the peak period and are divided into two periods with the day period spanning from 8am to 10:59pm and the night period from 11pm to 7:59am.

In addition to variation in price throughout the day is variation in price between treatment groups. Households in Treatment Group A have the highest night-time rate of €0.12/kWh and daytime rate of €0.14/kWh and these rates decrease with each group. However, with having the highest off peak rates it also has the lowest peak rate of €0.20/kWh and increases with the next group. I expect that households in Group D, with the highest peak rate and lowest off peak rates, will reduce their peak usage the most.

Each household in the treatment group is also assigned to an information stimulus group that provides household usage and billing in the form of a monthly, bi-monthly, and in-home display.[2] In addition to a utility bill, households also

[2]The IHD relays real time information every 30 minutes on current electricity usage and cost. The monitor includes a preset budget setting mechanism that allows households to set maximum daily spending amount on electricity.

receive an energy usage statement that provides detailed information on their usage and tips on how to reduce their electricity usage. The effects of these treatments are averaged, as I am only looking at the effects of TOU pricing on usage in this paper. Assignment to the information treatment is orthogonal to the pricing scheme assignment.

Participants completed pre- and post trial surveys that gathered socio demographic data about the respondent and household. Questions include respondents age, gender, employment status, and income bracket. These questions also cover household characteristics such as the square footage of the house, number of people residing in the home, types of fuel used for space heating and cooking, number of electronics and appliances. A majority of the questions in the second half of the survey assess usage behavior during the trial. I will be mainly utilizing information gathered from the pre-trial survey.

3.4 Methods

3.4.1 Research Question and Econometric Model

The goal of this paper is to examine the effects of time-of-use pricing on household energy consumption in an area that had time-constant pricing before the implementation of the trial. I ask three research questions. First, I am interested in whether there is a significant reduction in peak usage when the price of electricity is the highest. Second, I am especially interested in whether this reduction in peak usage is a reduction in overall usage or a shift in usage to another period of the day. I use difference-in-differences to estimate the average treatment effects for the following model:

$$Y_{ihdmyw} = \alpha_i + \theta_h + \rho_w + \phi_{my} + \gamma S_{dmy} + \sum_{p \in P} \sum_{t \in T} \beta_{p,t}([Period_h]_p \times [TREAT_{iy}]_t) + \epsilon_{ihdmyw} \tag{3.1}$$

where Y_{ihdmyw} is the natural log of household is hourly electricity usage in kWh for period P of each weekday w, day d in month m of year y, S_{dmy} is a vector of seasonal variables including an indicator for a bank holiday, the natural log of heating degree-days and daylight hours, θ_h are dummies for the period of the day, ρ_w denotes day of the week dummies, and ϕ_{my} is a set of month-year dummies. Observations where residents of the household are away from home determined by a daily usage that is below 0.1 kWh for 12 consecutive days or more are dropped from the analysis. $Period$ is a vector of dummy variables for the four periods of the day, $P \in Day1, Peak, Day2, Night$. $TREAT$ is a vector of dummy variables that equals 1 for whether household i is assigned to tariff treatment, $T = A, B, C, D$, during the trial period and 0 for the control group and all observations in the pre-trial period.

The coefficients $\beta_{p,t}$ are the average treatment effects by period of the day P and tariff treatment T. Finally, ϵ_{ihdmyw} is an unobserved error term. The model results are reported using the "within" estimator. I estimate Model 1 separately for weekday and weekend observations to account for differences in daily routines. I cluster all standard errors at the household level.

I estimate additional specifications to assess for the robustness of the estimates.

First I estimate Equation 3.1 for weekdays where I use day of the trial fixed effects (373 dummies, excluding holidays). Next, I limit the observations to period between July 14 and December 31 in 2009 and 2010. This is because baseline data in 2009 was only gathered for this period.

Similar to that of Houde et al. (2013), I estimate the treatment effects each individual hour of the day to gain further insight on electricity usage, reductions, and increases for specific hours of the day. In doing so, I can observe whether during which times the greatest increases and decreases in usage occur and whether there are formation of new peaks. I regress a model similar to that of Equation 3.1 to obtain hourly treatment effects by aggregating the treatment group and interacting them with the hours of the day:

$$Y_{ihdmyw} = \alpha_i + \theta_h + \rho_w + \phi_{my} + \gamma S_{dmy} + (\theta_h \times TREAT_{iy}) + \epsilon_{ihdmyw} \tag{3.2}$$

where the interaction term is allowed to take on different coefficients depending on the different hour of the day, where $h = 1, , 24$.

My study design relies on the common trends assumption, which I test. I run a fixed effects panel regression with a time trend to ensure that preexisting trends across the control and treatment groups are similar prior to the start of the trial. I regress the natural log of usage on the day of the year dummies interacted with $TREAT$ before the treatment period:

$$Y_{ihdmyw} = \alpha_i + \theta_h + \rho_w + \phi_{dm} + \gamma S_{dm} + (\phi_{dm} \times TREAT_i) + \epsilon_{ihdmyw} \tag{3.3}$$

where ϕ_{dm} is a vector of day by month dummies. I test the null hypothesis that the coefficients on $(\phi_{dm} \times TREAT_i)$ are jointly equal to zero.

3.4.2 Heterogeneous Peak Effects

My third research question is about the driving forces of the peak period treatment effects. I check for heterogeneous effects for different households by estimating the following two-step estimation procedure. I estimate a modified version of Equation 3.1:

$$Y_{hdmyw} = \alpha_i + \theta_h + \rho_w + \phi_{my} + \gamma S_{dmy} + \sum_{p \in P} \beta_p([Period_h]_p \times post_y) + \epsilon_{hdmyw} \quad (3.4)$$

for each individual household i, a total of 3,334 regressions. This difference approach compares a household with its usage from before and after the treatment period to obtain individual β^{Peak}. The β^{Peak} for each household is regressed on household characteristics using OLS with heteroskedasticity-robust standard errors.

In the second step, I estimate the following model:

$$\begin{aligned}\hat{\beta}_{Peak,i} =& \gamma_0 + \gamma_1 Age1_i + \gamma_2 Age2_i + \gamma_3 RTA_i + \gamma_4 RTB_i + \gamma_5 RTC_i + \gamma_6 RTD_i + \\ & \gamma_7 ThirdEdu_i + \gamma_8 Res_i + \gamma_9 Employ_i + \gamma_{10} Homeowner_i + \gamma_{11} FloorSqft_i + \\ & \gamma_{12} MissingSqft_i + \gamma_{13} DetHouse_i + \gamma_{14} Bdrms_i + \gamma_{15} Appls_i + \gamma_{16} Elecs_i + \\ & \gamma_{17} ElecHeat_i + \epsilon_i\end{aligned} \quad (3.5)$$

where $Age1$ and $Age2$ are indicator variables for respondents between ages 18 to 35 and 36 to 55, respectively, $ThirdEdu$ is an indicator for respondents with at least a third level education equivalent to a college degree, Res is the number of residents residing in the household, $Employ$ is an indicator for whether respondent is employed, and $Homeowner$ indicates whether the respondent owns or pays mortgage on the place of residence. Additionally, RTA, RTB, RTC, and RTD are indicators for households assigned to one of the four TOU treatment groups. A variable for income is omitted due to inconsistencies in survey reporting.

Household characteristics include $FloorSqft$ for the square footage of the home. This variable has a large number of missing observations as this question may be left blank if the respondent did not know the size of his/her home or did not wish to respond to the question. In order to prevent households with missing values from being dropped from the analysis, the missing values in $FloorSqft$ are recoded to zero and a dummy, $MissingSqft$, is used to indicate whether a household is missing square footage information. Other household characteristics include the number of bedrooms $Bdrms$, appliances $Appls$, and electronics $Elecs$, and $DetHouse$, which is an indicator for a detached house or bungalow. Additionally, a dummy $ElecHeat$ is included for households that rely mainly on electric space heating to warm their homes during winter months. An income variable is omitted due inconsistencies in reporting.

3.4.3 Quantile Regression and Conditional Average Treatment Effects

As utilities have limited information about their customers' socio economic information, it is difficult to target customers who will be the most responsive to pricing policies based on these characteristics. However, utilities are able to separate the low users from the high users with historic electricity consumption data. By exploring heterogeneity based on usage in response to price, we can gain insight on the customers who are most responsive to treatment.

Literature suggest that households may be able to take advantage of the lower off peak pricing and increase their overall usage all the while reducing their energy bills [5, 73]. Other studies have found no effects as reductions in usage during peak times are offset by increases in usage in other times [68], and in some cases, the lowest users are able to increase their overall daily usage [35]. If this were the case, then this would suggest that TOU pricing might allow the lowest electricity users to re-optimize consumption.

Highest users will have the most leeway in reducing usage than middle and low users [43]. This is consistent with studies that argue that it gets harder to reduce their usage after a certain point, more than just changing habits without upgrading appliances and investing in energy efficient retrofits [9, 40, 54].

The estimation of panel fixed effects quantile regression is adapted from a two-step estimation procedure developed by Ivan Canay (2011) to determine whether treatment effects vary across light and heavy electricity users. My adaptation is similar to that of Alberini et al. (2016):

$$Pr(Y_{it} \leq x_{it}\beta(\tau) + \alpha_i | x_{it}, \alpha_i) = \tau \tag{3.6}$$

where τ is a specific quantile. I analyze usage at the septiles.

By the assumption that the fixed effects are independent of τ, the model can be written as:

$$Y_{it} = x_{it}\beta_\mu + \alpha_i + u_{it}. \tag{3.7}$$

In this two-step estimation procedure, the dependent variable is transformed into $Y_{it} - \hat{\alpha}_i$, where $\hat{\alpha}_i$ are the estimated household fixed effects from "within" estimation in the first step [6]. In the second step, β_μ is estimated with quantile regression. Estimates produced by the two-step estimator are consistent and asymptotically normal [15].

Wichman (2015) models heterogeneity in residential water demand and discusses concerns about the strong assumption of rank preservation necessary for the validity of FE quantile regression estimates. Rank preservation means that if each household was ranked by their usage, this order must be preserved over time. In this case, this condition is weakly met in that some users ranks may change in response to the treatment but their assigned septiles are assumed to be preserved.

In addition to FE quantile regressions, I estimate conditional average treatment effects with the following model:

$$Y_{idmyw} = \alpha_i + \theta_h + \rho_w + \phi_{my} + \gamma S_{dmy} + \sum_{q \in Q} \beta_q([S_{idmy}]_q \times TREAT_{iy}) + \epsilon_{ihdmyw} \tag{3.8}$$

where β_q captures the conditional average treatment effects depending on the different septile, indicated by a vector of dummies in S_{idmy}. Equation 3.8 is a modification of Equation 3.1 with observations aggregated to the daily level, all else the same.

3.5 Data

3.5.1 Electricity usage data

I use hourly electricity consumption data extensively in my analysis. The baseline data are collected from July 14 through December 31, 2009. Treatment period data were collected from January 1 through December 21, 2010. The Commission for Energy Regulation in the Republic of Ireland reports that the average household uses 5,067 kWh of electricity in 2009 [72].[3] The average daily consumption of the households in the sample range from 11.67-12.26 kWh are calculated from the baseline data from July to December 2009. The households in this sample use roughly estimated at around 4,258 to 4,475 kWh in 2009, less electricity than the country average. This is a lower bound as I expect electricity usage to be higher during the winter months of January through early March that is not captured in the baseline

[3]Information from the World Energy Council and Enerdata show that Irelands 2009 annual household electricity consumption (at 5,157 kWh, slightly higher than what is reported by the SEIA) to be to be similar to that of Belgium (4,405 kWh), the UK (4,525 kWh), and France (5,374 kWh). On average, Irish households consume more than Italy (2,772 kWh), Germany (3,459 kWh), Greece (4,030 kWh), and Spain (4,147 kWh) but less than Sweden (8,888 kWh), Canada (11,083 kWh), the US (12,283 kWh), and Norway (16,844 kWh).

data.

Table 3.1 breaks down the baseline usage by hour for each period of the day for weekend and weekdays. The Day1 period shows lower usage than the Day2 rate for the weekdays. This is not surprising as the hours during the Day1 periods are also the same hours people attend school and work. This is graphically depicted in Figure 3.1(a). The same pattern is not reflected in Figure 3.1(b) where there is more fluctuation in the average daily weekend usage throughout the course of the day.

Figures 3.1(a) and 3.1(b) show the hour-by-hour usage for the pre trial and trial (treatment) period for the treatment group. Usage is noticeably more spread out during the course of the day during weekends whereas there is a sharp increase in usage during the peak period during the weekdays. Without accounting for season and unobserved heterogeneity of the households, the figures show a majority of reductions occur between 4 pm and 10 pm and slight increases in usage at night.

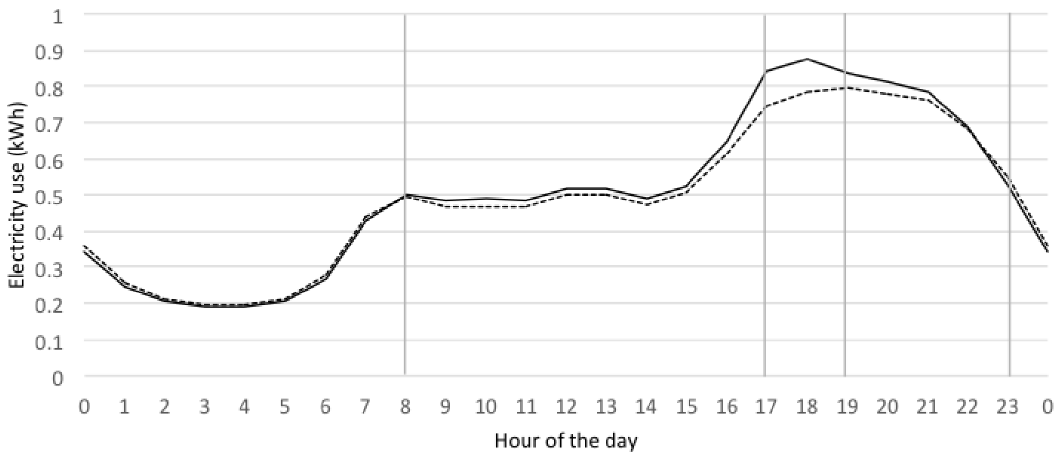
3.5.2 Weather and household variables

The temperature in Fahrenheit is an average of the average daily temperature from the Cork, Dublin, Galway, and Shannon weather monitoring stations. The temperature correlations between the stations range from 0.963-0.980, suggesting that it is reasonable to use a single average value of the observations from each station. The year 2009 was a warmer year than 2010 with annual average heating

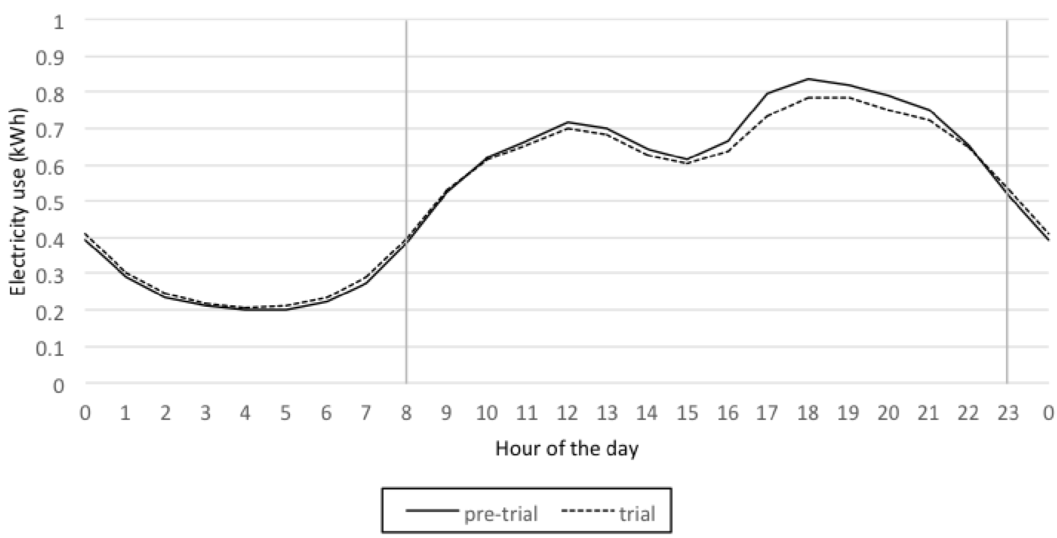
	Treatment		Control		p-value	Population
	Mean	(S.D.)	Mean	(S.D.)		
Day1 weekday usage	0.51	(0.62)	0.49	(0.60)	0.01	-
Peak weekday usage	0.85	(0.85)	0.80	(0.82)	0.03	-
Day2 weekday usage	0.78	(0.71)	0.74	(0.71)	0.02	-
Night weekday usage	0.29	(0.37)	0.27	(0.35)	0.00	-
Day weekend usage	0.68	(0.75)	0.65	(0.74)	0.00	-
Night weekend usage	0.28	(0.34)	0.27	(0.33)	0.00	-
Demographics						
No. of residents	3.07	(2.21)	2.86	(2.20)	0.02	2.70
Age of respondent 18-35 (%)	11.00	(0.31)	9.46	(0.29)	0.21	22.27
Age of respondent 36-55 (%)	46.98	(0.50)	41.79	(0.50)	0.01	41.19
No formal education (%)	1.36	(0.12)	1.64	(0.13)	0.58	36.53
Primary education (%)	10.88	(0.31)	15.32	(0.36)	0.00	1.36
Secondary education (%)	47.13	(0.50)	47.61	(0.50)	0.82	16.40
Third level education (%)	40.63	(0.49)	35.43	(0.48)	0.01	49.50
Employed (%)	52.07	(0.49)	53.91	(0.50)	0.00	28.89
Unemployed (%)	8.79	(0.28)	7.29	(0.26)	0.17	11.03
Retired/caretaker (%)	29.15	(0.45)	38.80	(0.48)	0.00	23.44
Housing Characteristics						
Homeowner (%)	92.99	(0.25)	93.34	(0.25)	0.73	69.70
No. of bedrooms	3.47	(0.83)	3.42	(0.87)	0.16	-
Apartment (%)	1.65	(0.13)	1.96	(0.14)	0.58	10.74
Semi-detached home (%)	33.42	(0.47)	29.11	(0.45)	0.02	27.61
Detached home/bungalow (%)	50.33	(0.50)	54.44	(0.50)	0.04	42.31
Terraced home (%)	14.60	(0.35)	14.49	(0.35)	0.94	17.04
No. of appliances[a]	6.09	(1.90)	6.01	(1.91)	0.27	-
No. of electronics[b]	4.08	(2.30)	3.72	(2.23)	0.00	-
Electric space heating[c] (%)	6.88	(0.25)	7.68	(0.27)	0.46	8.49
Electric water heating[d] (%)	62.36	(0.48)	61.85	(0.49)	0.80	-

Note: [a]Appliances, include dryers, washers, dishwashers, electric cookers, freezers, and water pops top, are coded at 3; [b]Electronics, include televisions, computers, laptop, and game consoles, are top coded at 4; [c]Electric heating includes central heating, storage heating, and plug-in heaters; [d]Electric water heating includes central, immersion, or instantaneous water heater. Household population statistics are from the 2011 Census reported from the Irish Central Statistics Office. For the population statistics, Age is percentage of population between ages 18-35, 36-55, and 56 and up; percentage of education is based on education level of people over the age of 15.

Table 3.1: Summary Statistics



(a) Weekday Hourly Usage



(b) Weekend and Holiday Hourly Usage

Figure 3.1: Weekday and Weekend Hourly Usage Comparison for the Treatment Group

degree-days of 5794.85 and 6414.95, respectively. The moderate temperatures of Ireland do not go above 65 F and thus do not require a variable for cooling degree-days. In addition to controlling for the temperature, I also control for the number of hours of daylight, which averages 4486.19 hours of daylight per year.

A pre-trial survey was conducted to gather socio-demographic information and structural characteristics of the home information. A total of 2,755 households completed the survey, an 82.6 percent response rate. Chapter 2 Table 5 compares the summary demographic and housing characteristic information across the treatment and control households. T tests reveal that Treatment households tend to be younger, employed, and more educated. Electricity consumption by hour is up to 6 percent higher among treatment households. However, these differences and other unobservable characteristics are assumed to be time constant and can be controlled for using individual household fixed effects.

In comparison to the population statistics in Ireland in the last column of Table 3.1, households in the trial are older, more educated, and more likely to own a single-family home than the average household in Ireland. Employment, number of residents, and electric space heating in the sample are similar to the population averages. One concern is whether findings are representative of the entire population as trial participation was voluntary.

3.6 Results

3.6.1 Results from the Difference-in-Difference Approach

A pre-treatment trends check between the treatment and control groups is conducted to determine whether there are significant differences in trends between the two groups. I estimate Equation 3.3 and failure to reject the null means no evidence of difference trends, $F_{169,3419} = 0.99, p = 0.53$.

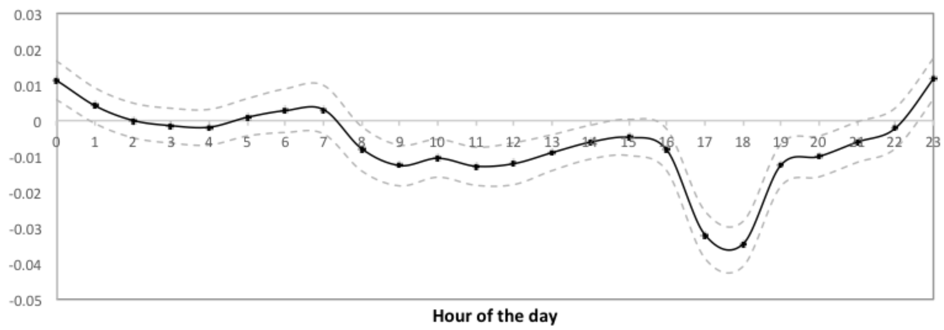
Results from the panel fixed effects difference-in-differences Equation 3.1 are reported in Table 3.2 Column 1 where reductions during the Day1 period are significant for Treatment Groups A and C of 0.80 percent and 0.60 percent per hour of the period, respectively. I find significant reductions of similar magnitude for the Day2 period for Treatment Group B and D of 1.19 and 1.00 percent reduction per hour. These estimates are consistent with economic theory in that Group A will have a larger reduction than Group C in that Group A has a higher day time rate than Group C. The same concept applies for Groups B and D. However, it is uncertain as to why reductions occur during Day1 for Groups A and C whereas significant reductions occur during Day2 for Groups B and D. One reason may be due the sample size of the treatment groups in that Groups A and C is over twice the number of households in Groups B and D. While these coefficients are jointly different from 0, they are not jointly different from each other during their respective periods of the day.

Next, I look at the peak period effects to address one of the main questions

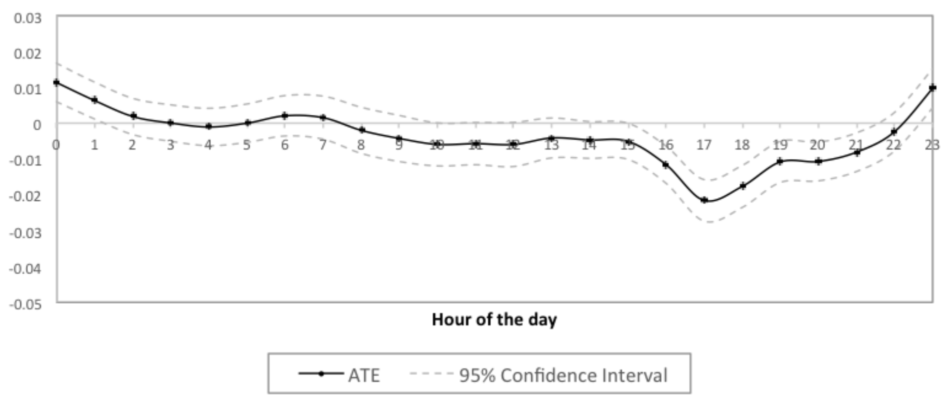
Ln(usage)	(1) FE, Wk		(2) FE, Wknd		(3) FE, DOT		(4) FE, Baseline		(5) FE, Wk, Survey	
Day1										
RTA	-0.008***	(0.003)	-0.006	(0.003)	-0.010***	(0.003)	-0.008***	(0.003)	-0.006**	(0.003)
RTB	-0.006	(0.004)	-0.004	(0.004)	-0.008*	(0.005)	-0.005	(0.005)	-0.004	(0.005)
RTC	-0.006**	(0.003)	-0.004	(0.003)	-0.008***	(0.003)	-0.003	(0.003)	-0.005	(0.003)
RTD	-0.006	(0.004)	-3.53E-04	(0.004)	-0.008*	(0.004)	-0.005	(0.005)	-0.009**	(0.004)
Peak										
RTA	-0.027***	(0.004)	-0.020***	(0.004)	-0.029***	(0.004)	-0.027***	(0.005)	-0.028***	(0.005)
RTB	-0.029***	(0.007)	-0.018***	(0.006)	-0.031***	(0.007)	-0.028***	(0.007)	-0.032***	(0.008)
RTC	-0.033***	(0.004)	-0.014***	(0.004)	-0.035***	(0.004)	-0.030***	(0.005)	-0.036***	(0.005)
RTD	-0.038***	(0.007)	-0.016***	(0.006)	-0.040***	(0.007)	-0.039***	(0.008)	-0.043***	(0.008)
Day2										
RTA	-0.004	(0.004)	-0.003	(0.003)	-0.006*	(0.004)	-0.006	(0.004)	-0.004	(0.004)
RTB	-0.012**	(0.006)	-0.013**	(0.005)	-0.014**	(0.006)	-0.012*	(0.006)	-0.010	(0.006)
RTC	-0.003	(0.004)	-0.003	(0.003)	-0.005	(0.004)	-0.004	(0.004)	-0.003	(0.004)
RTD	-0.010*	(0.006)	-0.014***	(0.005)	-0.013**	(0.006)	-0.014**	(0.007)	-0.009	(0.007)
Night										
RTA	0.003	(0.003)	0.005**	(0.003)	0.001	(0.003)	0.002	(0.003)	0.005	(0.003)
RTB	0.002	(0.005)	0.002	(0.005)	2.28E-04	(0.005)	3.92E-04	(0.005)	0.003	(0.005)
RTC	0.007**	(0.003)	0.007**	(0.003)	0.005*	(0.003)	0.007*	(0.003)	0.010**	(0.003)
RTD	0.009**	(0.004)	0.008	(0.005)	0.007	(0.005)	0.008	(0.005)	0.013***	(0.005)
Ln(hdd)	S(+)		S(+)		No		S(+)		S(+)	
Holiday	S(+)		S(-)		No		S(+)		S(+)	
Daylight	S(-)		S(-)		No		S(-)		S(-)	
Period of the day FE	Yes		Yes		Yes		Yes		Yes	
Day of the trial FE	Yes		No		Yes		No		No	
Day of the week FE	Yes		Yes		No		Yes		Yes	
Month × year FE	Yes		Yes		No		Yes		Yes	
SER	0.289		0.303		0.289		0.291		0.288	
No. of households	3,334		3,334		3,334		3,334		2,755	
Observations	30,685,632		11,985,216		30,685,632		19,652,928		25,367,376	

Standard errors in parenthesis. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table 3.2: Main Effects



(a) Weekday Average Treatment Effects by Hour



(b) Weekend Average Treatment Effects by Hour

Figure 3.2: Average Hourly Treatment Effects

in this study. I find that increasing the peak period price for Treatment Group A results in a 2.66 percent reduction per hour of the peak period. The increase in peak period price corresponds to increasingly larger reductions with the Group B with a 2.86 percent reduction, Group C with a 3.25 percent reduction, and Group D with a 3.73 percent reduction per hour. However, despite the different tariff schemes, these estimates are not jointly different from each other, $F_{3,333} = 0.71, p = 0.5477$.

Finally, a slightly increased but significant usage of 0.70 to 0.90 percent per hour from Treatment Groups C and D during the night period. On average, night period treatment effects for all groups appear to be small and vary in significance, which is not surprising given that these estimates are the average effects of 9 hours. Figure 3.2(a) shows the average treatment for the combined treatment groups by hour. The first hour of the night period show an increase of 1.18 percent whereas the estimates for the hours following are insignificant. This suggests that households shift some of their peak consumption to the hour directly after the Day2 period when the price of electricity is at its lowest.

I find that increasing a temperature by 1 heating degree-day increases electricity usage by 0.009 percent. This minute effect may be due to the fact that only 1.85 percent of households in our sample rely on electricity for heating through central heating and plug in heaters. In addition, longer daylight hours imply a reduction in electricity usage as longer daylight hours generally indicates delaying turning on lights and more time spent outdoors.

Column 2 shows the average period treatment effects for the weekend to be insignificant during the Day1 period, some reduction for Groups B and D during the Day2 period, and some increase for Groups A and C during the night. The surprising element is the significant hourly reduction in the peak period across all four treatment groups ranging from 1.39 to 1.98 percent. When broken down to the hourly average effects, shown in Figure 3.2(b), the figure largely resembles that of the weekday hourly treatment effects. The effects are insignificant for most of the 2am through 4 pm followed by significant reductions from 4 to 10 pm. One possible reason for this is the formation of habits around the peak pricing periods that carry over from the weekdays to the weekend when peak pricing is not in effect. Another reason can be that the period after 4pm is when residents are home and thus respond to higher day prices. These reasons can only be taken as conjectures, as there is not sufficient information available to support the claims or discrimination between them.

I test the robustness of the results from Model 1 with two other specifications. I first estimate Equation 3.1 using day of the trial fixed effects for a more flexible model, shown in Table 3.2 Column 3. I find that estimates closely resemble that of Equation 3.1. Second, I restrict the data set to only observations from July 14 through December 31 to have a more accurate analysis of the before and after trial period for the treatment and control groups. These results also closely resemble that of Equation 3.1.

Finally, I consider a specification where I look at households that completed the pre-trial survey. This is because analyses reported below are conducted using information from the survey and households with missing values are dropped from the regression, thus losing 579 households. I find average treatment effects for the peak period to yield the largest reductions as well as largest increases during the night compared to the other specifications. This suggests that households that completed the pre-trial survey may have originally been more interested in their electricity usage or completing the survey raised awareness of their electricity usage patterns, resulting in larger responses to changes in price.

$\hat{\beta}^{peak}$	(1)		(2)		(3)	
Detached home	-0.009***	(0.003)	-0.008***	(0.003)	-0.007**	(0.003)
Employed	0.001	(0.004)	0.002	(0.004)	0.002	(0.004)
Homeowner	-0.008	(0.006)	-0.006	(0.006)	-0.005	(0.006)
RTA	-0.027***	(0.003)	-0.027***	(0.003)	-0.027***	(0.003)
RTB	-0.042***	(0.006)	-0.042***	(0.006)	-0.043***	(0.006)
RTC	-0.039***	(0.004)	-0.039***	(0.004)	-0.039***	(0.004)
RTD	-0.051***	(0.006)	-0.051***	(0.006)	-0.051***	(0.006)
Age 18-35	-0.004	(0.006)	-0.003	(0.006)	-0.004	(0.006)
Age 36-55	-0.008**	(0.004)	-0.007*	(0.004)	-0.008**	(0.004)
No. of residents	-0.008***	(0.002)	-0.008***	(0.002)	-0.007**	(0.003)
No of residents^2	0.001**	(2.29E-4)	0.001**	(5.74E-4)	0.001**	(2.41E-4)
No. of bedrooms	-0.008***	(0.002)	-0.007***	(0.002)	-0.006**	(0.002)
College educated	0.006*	(0.003)	0.007**	(0.003)	0.008**	(0.003)
Floor area sqft			1.42E-6*	(7.64E-7)	1.35E-6	(7.95E-7)
Missing floor			0.011***	(0.004)	0.010***	(0.004)
No. of appliances					-0.003***	(0.001)
No. of electronics					-1.35E-03	(0.001)
Electric space heating					-0.011*	(0.006)
Constant	0.043***	(0.008)	0.031***	(0.009)	0.040***	(0.009)
Observations	2748		2748		2748	
R^2	0.079		0.82		0.087	

Standard errors in parenthesis. $*p < 0.10, **p < 0.05, ***p < 0.01$ Note: Variables for appliances and electronics are top coded.

Table 3.3: Effects of Household and Structural Characteristics of the Home on Peak Effects

3.6.2 Heterogeneous Peak Effects

I report the results from Equation 3.5 in Table 3.3 for peak effects. The dependent variable is the effect of the TOU treatment on the peak period; therefore a negative coefficient should be interpreted to increase the effect on peak usage whereas a positive coefficient will reduce the effect on peak usage. Columns 1 and 2 include independent variables for respondent and family characteristics and structural characteristics of the house. Being a homeowner does not impact peak effect, suggesting that, all else the same, there are no differences between renters and homeowners on peak usage. However, having a detached home does result in higher reductions in peak consumption. These households may have more autonomy over the electricity usage in their homes. Contrary to expectation, respondents who are college educated reduce peak usage less than households without a college education. Respondents aged 36-55 have a larger reduction than those above 56. Having more residents in a household increases the peak effect but at a decreasing rate. As expected, being in a treatment group results in larger reductions during the peak period compared to households in the control group.

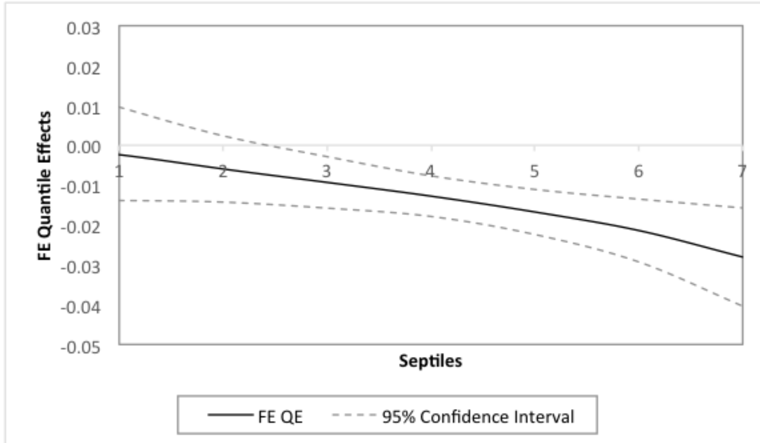
Table 3.3 Column 1 omits the $FloorSqft$ and $MissingSqft$ variables as 58.19 percent of respondents did not know or did not wish to report the size of their homes. It is also possible that misreporting errors were present with the 42 percent who were able to answer the question. However, including the two variables shows robustness in the estimates in Column 2. The coefficient $FloorSqft$ indicates the larger homes have lower peak effects, although weakly significant at the 10 percent level.

Finally, estimates in Table 3.3 Column 3 reveal significant impact of having more appliances results in a larger peak effect, but having more electronics do not. Households that rely mainly on electricity for space heating are capable of a larger impact on peak usage. Higher peak pricing may encourage households to increase their heating during periods prior to and after the peak period while reducing heating during the peak period.

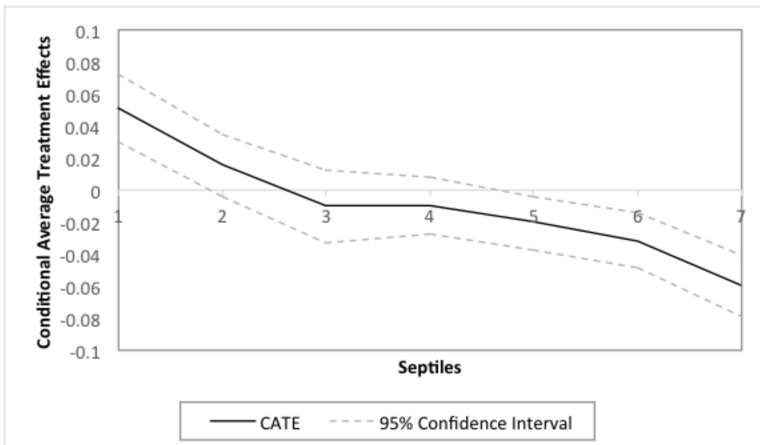
3.6.3 Results for Fixed Effects Quantile and Conditional Average Treatment Analysis

I graph the coefficients on the treatment variable for the septiles from fixed effects quantile regression as described in Equation 3.7. Figure 3.3(a) shows a decreasing trend with the lowest 25 percentile of households exhibiting the smallest and statistically insignificant effects. Households in the top 12.5 percentile exhibit the highest effects.

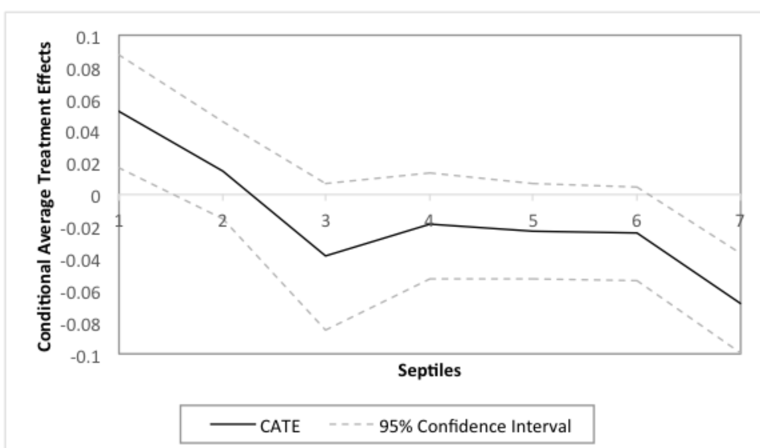
Alternatively, I present estimates for the conditional average treatment effects for the septiles of 2009 baseline usage in Figure 3.3(b). The results are broadly consistent with those of the FE quantile estimates reflecting a downward trend in effects. The highest septiles, bottom 12.5 percentile of users exhibit a statistically significant average increase of 5.23 percent whereas the second to fourth septiles exhibit no significant effects. The top 12.5 percentile of users exhibit the highest negative effects of 5.82 percent.



(a) FE Quantile ATEs on Septiles of 2009 Usage



(b) ATEs Conditional on Septiles of 2009 Usage



(c) ATEs Conditional on Septiles of 2009 Usage for College Educated Respondents

Figure 3.3: Fixed Effects Quantile Regression and Conditional ATEs

	Control			Treatment		
	2009	2010	% change	2009	2010	% change
August	321.95	314.4	-2.40%	338.47	323.82	-4.33%
	€45.40	€44.33	-2.41%	€47.72	€44.68	-6.37%
September	308.18	319.49	3.54%	327.1	330.77	1.12%
	€43.45	€45.05	3.55%	€46.12	€46.03	-0.20%
October	339.34	333.75	-1.67%	360.38	346.85	-3.75%
	€47.85	€47.06	-1.68%	€50.81	€48.19	-5.16%
November	378.08	353.67	-6.90%	400.13	364.96	-8.79%
	€53.31	€49.87	-6.90	€56.42	€52.00	-7.83%
December	446.42	412.09	-8.33%	470.39	423.51	-9.97%
	€62.95	€58.10	-8.35%	€66.32	€60.29	-9.09%

Table 3.4: Average Monthly Usage (kWh) and Bill(€)

These effects are further emphasized for households whose respondent is college educated in Figure 3.3(c) where the first and seventh septiles exhibit larger effects of 5.42 percent increase and 6.63 percent decrease, respectively. Unlike Figure 3.3(b), septiles in between do not exhibit any significant effects. More educated households may be better at understanding prices and how their electricity consumption patterns impact their overall bill. Users in the first septile or the bottom users may be more efficient in reducing electricity during the peak period all the while increasing their usage during off peak periods, resulting in higher increase in usage than average effects of the full sample. These findings are consistent with Di Cosmo et al. (2014) and Ito (2011).

I compute average monthly usage and bills for the treatment and control groups and report them in Table 3.4. They refer to August through December with complete pre and post trial data. For every month with the exception of September, monthly usage and bill in 2010 declined for both Control and Treatment group. September of 2010 saw an average increase in usage for both control and treatment groups from 2009. Despite this, there was an average decrease in the bill for the treatment group compared to an increase in the bill for the control group from the previous year. On average, households under TOU in the treatment group were able to increase their overall monthly usage while decreasing their total bill. While a majority of households in the treatment and control groups received bi-monthly bills, this comparison is not meant to analyze effect of billing frequency and information on usage.

3.7 Conclusion

In this paper, I analyze the effects of TOU pricing in a region that has never experienced this type of pricing scheme before. Ireland is a temperate region with mild winters and cool summers where temperatures during this study do not fall below 22°F or exceed 65°F. In other countries where there is greater seasonal variation and larger reliance on electric heating, heating and cooling may drive effects of TOU pricing. I find evidence that TOU is still effective in a region where electricity is not the main fuel used for heating and does not require air-conditioning for cooling. The effect of peak period pricing, is however, modest. It is possible that TOU may produce larger effects in areas that use air conditioning and electric space heating.

In the Irish Trial, households that were on TOU pricing reduce their consumption by 2.66 to 3.73 percent for each hour during the peak period. Effects increase by tariff group which face increasing differences between the peak and day prices. Hourly estimates show evidence of load shifting from the peak and day periods to the beginning of the night period. I find no evidence of load shifting of usage from the weekday to the weekend suggesting reductions in overall usage. Surprisingly, results also show that the peak effects also occur on the weekend at lower magnitudes. In other words, households reduce their usage during weekday designated peak hours, which carry over to the weekend suggesting evidence of changes and formation of new habits. Weekend reductions may also be corresponding to periods when household members are active at home. Overall, the effects are generally small compared to CPP studies that have found reductions from events to range from 7 to 16.2 percent [51, 53, 78]. Real time pricing has been found to be more effective for conservation measures than for load shifting [7].

I investigate the source of heterogeneity in the response to TOU pricing. I find that the type of housing structure, size of the house, age and education of survey respondent and total appliances in the home significantly impacts effects on peak usage. These are opposite to the findings of Houde et al. (2011) and Davis (2011), who do not find survey variables to be significant sources of heterogeneity.

Households that consume the lowest electricity in kWh are more likely to increase their overall consumption whereas households on the higher end of consumption have the largest reduction effects. In some circumstances, TOU pricing may be beneficial to low users. It may allow for them increase their overall usage and level of comfort without increasing their bill, particularly in households located in areas with extreme temperatures. Being able to increase the comfort levels in their homes can lower mortality rates particularly for children, the elderly, and poor [21, 41, 42]. When these patterns of response to TOU are observed, TOU is the most effective at smoothing peak demand when reductions for the high-end users are greater that the increases from the low-end users.

Overall, TOU may also be more effective for reducing usage of the highest users and useful for targeting purposes, as some households are more responsive to TOU than others. However, caution is needed in interpreting these results as effects TOU pricing on peak load are small and are reflective of single-family households with educated heads of households of the working age. Results are not representative of the entire population since participation in the trial was voluntary and participants were compensated if their bills under TOU pricing were higher than if they were on a flat rate tariff. Feedback and energy efficiency policies may be combined with TOU to encourage further adjustments to usage beyond altering energy consumption habits. Additionally, reducing peak consumption has implications for savings in greenhouse gas emissions.[4] Further research requiring information on plant generation will be necessary to address these concerns.

[4]However, if more efficient generators or cleaner fuels, such as natural gas and renewables, are used to generate electricity to meet peak demand then programs that focus on shifting peak load to other periods where electricity is generated with low cost but dirtier generators, such as coal and fuel oil, may result in higher greenhouse gas emissions.

Chapter 4: The Effects of TOU Pricing on CO_2 Emissions and Generation

4.1 Introduction

The Republic of Ireland (IE) electricity market is the first of its kind in that in 2007, the two separate markets serving IE and Northern Ireland (NI) were integrated into a Single Electricity Market (SEM) for the island. The Commission for Energy Regulation (CER) mandates the SEM require electricity generators to sell electricity into a single spot market for the island in, "which all electricity generated on or imported onto the island of Ireland must be sold, and from which all wholesale electricity for consumption on or export from the island of Ireland must be purchased." The SEM is operated by the Single Electricity Market Operator (SEMO) and is responsible for paying generators for their electricity produced and invoicing suppliers for electricity purchased. Requiring all trading to occur in the SEM allows for more price and market outcome transparency, which are often obscured in European bilateral markets [20]. The SEMO market is a relatively isolated system with imported electricity treated as generation units that must be placed as a bid into the market. As a result, all electricity imported and exported to and from the island can be closely tracked.

The previous chapters emphasized the importance of curtailing peak load on emissions savings and reducing the need to increase capacity of generation to meet peak demand. In this chapter, I look at the make up of the island system to look at the implications of an island wide implementation of a residential TOU pricing policy. I estimate and compare the cost of generation and CO_2 emissions for four select weekdays in 2011 representing each of the four seasons. By using the generator technical parameters, heat rate requirements, and commercial offer data, I am able to build the merit curve for the sample days. I repeat this procedure on the adjusted load to simulate the loads under TOU pricing and compare with the actual load.

Simulation variable pricing studies have found that, in the short run, time-varying the price of electricity as it is generated results in average load increases, a decrease in profits for all generating sectors, an increase in consumer surplus, modest efficiency gains, and a decrease in CO_2 emissions [45]. Yet in the long run, efficiency gains usage are concomitant even with inelastic demand [13]. When examining short run, simulation studies, others have found that the distributions of electricity loads and prices becomes compressed, and as all rates decrease, the average loads increase. This implies decreases in profits for all generating sectors, consumers surplus increases for all consumers, modest efficiency gains, and the increase of SO and NO emissions and decrease CO_2 emissions [45].

Fuel mixes used to meet load generation demand may have implications on the impact of time varying pricing aimed to reduce within day variation. In Holland and Mansur (2008), regions where oil is predominantly used in the generation of electricity to meet peak demand have larger decreases in emissions than regions where peak demand is met by hydropower. Their findings further suggest that reducing peak demand in regions where more hydro is used to meet peak demand would result in increases in emissions as demand is shifted to other periods in which a dirtier generator is used to meet the demand. The SEMO consists of a similar fuel mix of hydro, oil, and gas used to meet peak demand suggesting that a policy that reduces within day variation of load may have positive or negative impacts on emissions.

4.2 Background

The objective of the SEM is to provide the least cost source of electricity generation at any point in time across the country by accessing the more efficient generators to meet demand [20]. This is important as more expensive and/or less efficient generators are used, too, during periods of high demand. Fossil fuels account for 80 percent of the islands electricity generation where the base load generation is powered by coal and peat[1], mid-merit generation met by natural gas combined cycle generation units, and peaking power generation is powered by oil and natural gas [17, 20]. Despite the remaining 20 percent of electricity generation powered by renewable energy from wind, bioenergy, and hydro [17], fossil fuels used in electricity generation is the second largest contributor of greenhouse gas emissions in Ireland, totaling 21.9 percent of national emissions [29].

In addition generators on the Island of Ireland, the Moyle Interconnector im-

[1]Peat generators are the dirtiest and most expensive to operate of the fuels. However, peat is subsidized in order to provide employment in the Midlands region of the Republic of Ireland and continues to be a topic of debate amongst politicians and economists [74].

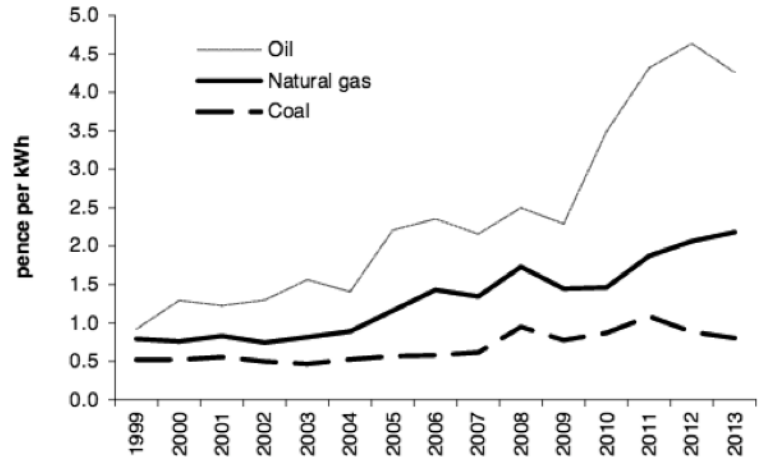
ports and exports electricity to and from Northern Ireland and Scotland. It has a capacity to import and export up to 500MW of electricity between Northern Ireland and Scotland. Between 2008 and 2011, electricity was mainly imported from Scotland. In mid-September 2011, the Moyle interconnector went out of service until February of 2012. The East West Interconnector is the other importation source of electricity to Ireland from Great Britain. It did not go online until September 2012.

According to the 2011 Republic of Ireland Census [1], these interconnectors deliver electricity to approximately 1,654,208 private residential households within the Republic of Ireland. And between 2008 and 2011, residential electricity consumption consists on average of 33 percent of the overall share of electricity consumed in Ireland [72]. The large portion of electricity consumed by these residences has significant implications as they relate to curtailing electricity demand and increasing efficiency gains in generation.

Interconnector units are scheduled and fixed a day ahead of the next scheduled run. In the SEM, wholesale prices are determined for every half hour. Generation plants bid in the day ahead market and generate electricity in the order ranked from lowest to highest by their bids until demand is met [25].

4.2.1 SEMO Merit Curve and Electricity Generation

Generator production and start up cost information submitted for each active generator on the island to the SEMO are used to calculate half hourly and total production costs. Plants (including available capacity submitted by the Moyle In-



Source: UK Department of Energy and Climate Change

Figure 4.1: Weekday and Weekend Hourly Usage Comparison for the Treatment Group

terconnector generator units) are allowed to submit up to 10 price and quantity pairs that define the cost of generation by increments and a no load cost.[2] These costs are associated with the generator heat rate curve.

The merit curve is created for each half hour of the day ranking priority dispatch generators, such as predicted wind generation and peat generators, followed by price making generators by least cost while taking into account their fixed technical parameters. Fixed technical parameters for each generation unit include minimum stable capacity and maximum stable capacity, minimum up and down time, and start up temperature (See Tables B.1 and B.2 in Appendix B). These parameters also play a role in determining generation unit position in the merit curve. For example, a condensing steam cycle generator (CSCG) uses fossil fuels to boil water to generate steam to run the turbine. They require the most energy to start up and

[2]Cost of generation varies by type of generator and price of fuel. A no load cost is the cost to run the generator per hour at 0 electricity output.

have the highest minimum on time requiring the unit to run for a fixed time before it can be powered down. These generators make up the baseload as long as coal is cheaper than natural gas (see Figure 4.1).

Combined cycle gas turbines (CCGTs) can be ramped up faster and require less energy to start up than CSCGs. These units make up the bulk of the mid-merit generators. Open cycle generators that use natural gas and distillate oil make up the peaking units as they have the lowest minimum on times and can be rapidly ramped up and down to meet peak demand. Hydro generator units have moderate ramp up and down rates and no minimum on times making them flexible generators for meeting base, mid-merit, and peak demand.

In addition to providing the SEMO with unit generation cost, plants had to also provide information on incremental heat rate slopes, no load heat rate, and generation increments. These variables are used to create the heat rate curve to determine the amount of energy required by each generator to produce a MW of electricity.

4.3 Data

As of 2011, the Island had a total of 73 grid-connected predictable generator units[3], 53 thermal and 15 hydro generators. Table 4.1 breaks down the fuel used for generation, unit type, and installed capacity for Ireland and Northern Ireland. Natural gas fueled generators have the largest capacity followed by coal. Distillate

[3]Wind generation is considered to be variable generation and is not counted as a predictable generator unit.

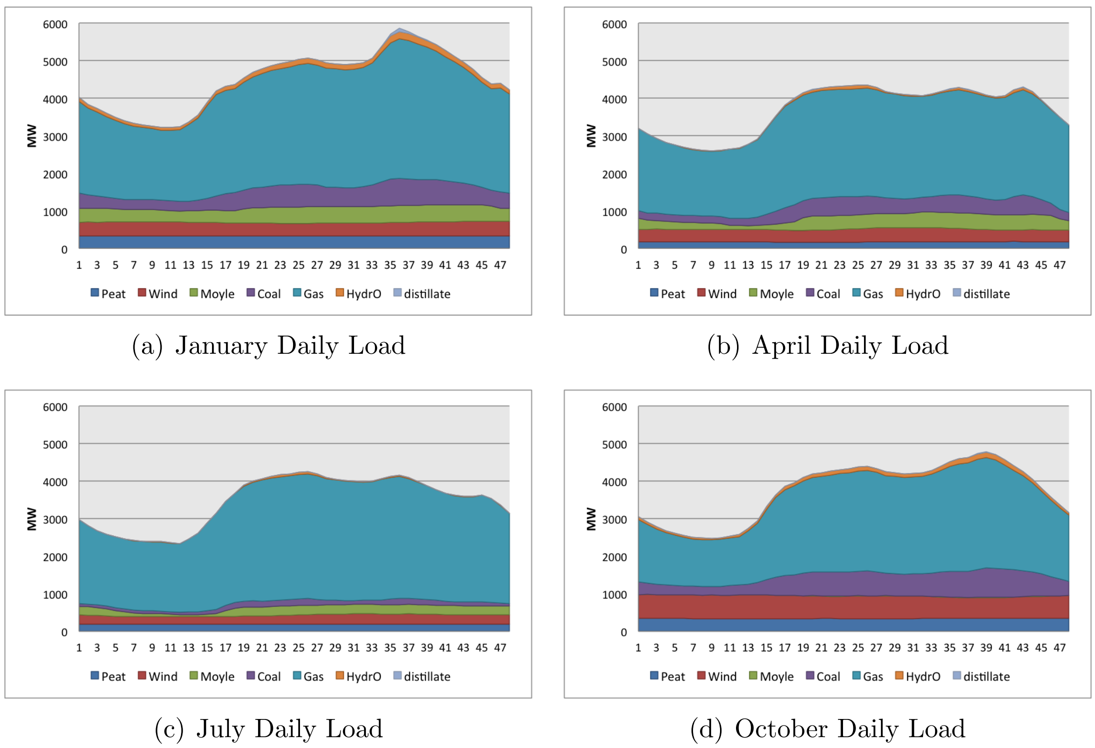
Fuel for generation	Unit Type	IE installed capacity (MW)	NI installed capacity (MW)	% of total capacity
Peat or peat/biomass	Baseload	345.6	-	3.99%
Coal	Baseload	840	476	15.20%
Natural gas	Baseload/mid-merit	3415.5	1,536	57.17%
Hydro/ pumped storage	Peaking/mid-merit	508	-	5.87%
Distillate	Peaking	424	315.2	8.54%
Oil	Peaking	800	-	9.24%

Table 4.1: Installed island system generation capacity by fuel

and oil make up the next largest thermal capacity.

Half hourly load data by generator unit is collected from the SEMO for January 12, April 13, July 13, and October 12, 2011. These days, shown in Figures 4.3(a)-4.3(d), represent a weekday for each season of the year to illustrate the difference in the shape of the daily load curve and fuel mix. Figures 4.2(a)-4.2(d) provide comparisons for the daily load and fuel mix averaged by month. In 2011, generation load is highest during the fall and winter months. Generators fueled by distillate oil are mainly used in the winter, spring, and fall months when peak demand days are more prominent. Generators fueled by heavy fuel oil are the dirtiest emitters of CO_2 and are used to meet peak demand on rare occasions. Initial analysis shows fuel oil is occasionally used as a peaking plant on the highest load days in January and is more often used as startup fuel. Figure 4.2(c) shows a decrease in the proportion of coal-generated electricity in July away from coal as demand is reduced. During months of lower demand, generation is met with primarily baseload and mid-merit generators. On this day, available gas generators were cheaper to run than coal generators.

The half hourly load data is used to calculate the CO_2 emissions produced



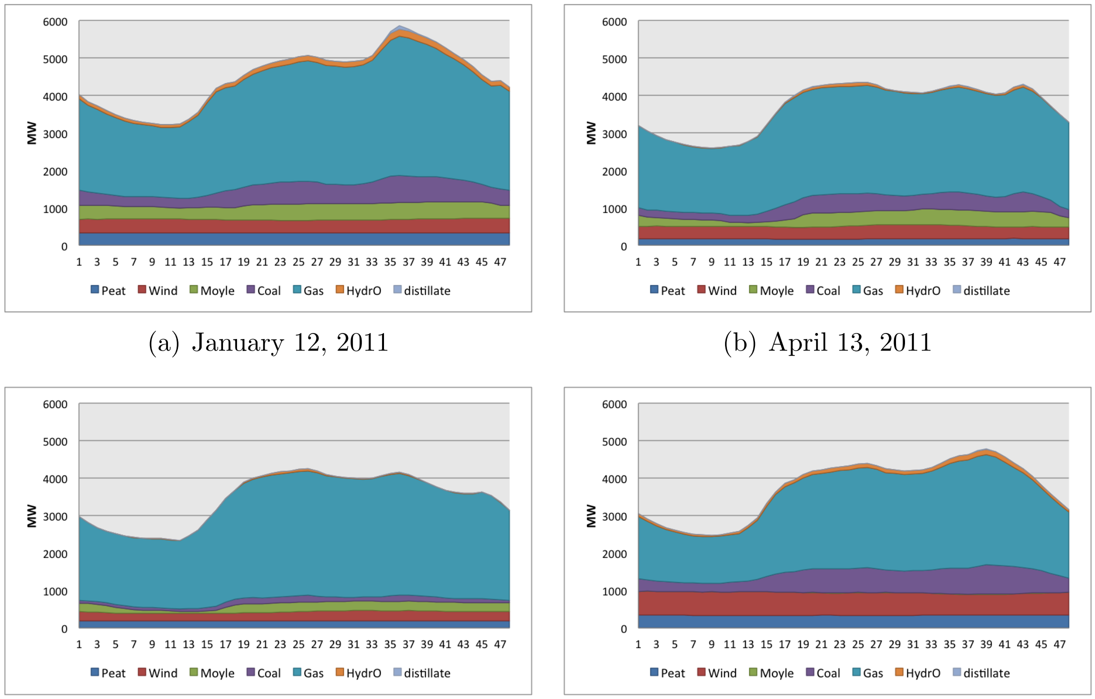
(a) January Daily Load

(b) April Daily Load

(c) July Daily Load

(d) October Daily Load

Figure 4.2: Average daily load duration curves and fuel mix for select months in 2011



(a) January 12, 2011

(b) April 13, 2011

(c) July 13, 2011

(d) October 12, 2011

Figure 4.3: Daily load duration curves and fuel mix for select days in 2011

in electricity generation. The methodology used is similar to that of Wheatley (2013) and Di Cosmo and Valeri (2016). I use individual plant information on load, incremental heat rates, and no load heat requirements to calculate a heat rate curve that determines the heat energy required to meet individual generator loads (from Allislandproject.com). The heat energy is converted to carbon dioxide emissions using energy factor conversions from the SEIA Annual Energy in Ireland report (see Table B.1 in Appendix B) [48].

The load data is also used with commercial offer data submitted by the plants for each generator unit for the SEMO to calculate generation costs. commercial offer data depends on the price of fuel, technical limitations of generation units, scheduled maintenance, etc. Since the data is in half hour increments, converting from MW to MWh requires the daily production cost to be divided by two. The no load cost, price and quantity pairs and maximum load were used to calculate the hourly operating rate less the start up costs to determine the merit curve. I use the following equation to calculate the daily production cost for each generator unit:

$$\text{Daily Production Cost for Generator Unit } i = \frac{1}{2}\sum_{h=1}^{48} NoLoad_{ih} + (P1 \times 1^{st} \text{ Increment})_{ih} + ... + (P_n \times N^{th} \text{ Increment})_{ih} \tag{4.1}$$

where the first increment is the measure between 0 and Quantity 1 (from the first price quantity pair), the second increment is the measure between Quantity 1 and Quantity 2 (from the second price quantity pair) less the first increment. For example, on January 12, 2011, the Aghada Combined Cycle Gas Turbine cost €35.62/MW for the first increment between 0-213MW, €45.08/MW for the increment between 213-430MW, €46.43/MW for the last increment between 430-448MW, and a no load cost of €4712.21/hour. Generating a load of 435MW of electricity for 1 hour would cost €22313.78 (€51.30/MWh) minus the startup cost.

4.4 Method

I simulate daily load under time of use response based off the average treatment effects estimated in Chapter 3 Figure 3.2(a) to calculate the percentage change in half hourly load, generation cost, and CO_2 emissions. In 2011, 33 percent of electricity consumed in the Republic of Ireland went to residential households. This statistic assumed to be islandwide implies an average 1 percent reduction to peak load, 0.30 percent reduction to day load, and a 0.35 percent increase in night time load.

Additionally, load shifting in response to the TOU pricing simulation is constrained within other times of the day and is not transferrable to other days. Wind and peat generators are scheduled first followed by the least cost generator units while taking into consideration startup costs, minimum stable capacity, and incremental costs. After calculating the MW reduction (increase) for each half hourly load resulting from a TOU scenario, I apply the reduction (increase) to the hourly merit curve. Load generation is reduced (increased) from the generating unit with the highest (lowest) incremental price. The least cost generator, usually a hydro unit or high efficiency gas generator but can also be a coal unit, is updated in the schedule to meet the increased load.

Startup cost and startup emissions were determined based on the number of hours the generators are off after the previous scheduled runtime. The hours off determine whether the generators start off cold, warm, or hot and are associated with different costs, a cold start being the most costly as it requires more energy to start.

4.5 Results and Discussion

Table 4.2 reports results for generation costs and emissions from generation. System generation load was highest in October due to the Moyle Interconnector

January 12, 2011	Actual Load	TOU Load	Savings
Total Load (MWh)	111,593.48	111,373.45	220.03
System Generation Load (MWh)	89,028.77	88,808.74	220.03
Generation cost (€)	4,372,533.34	4,357,172.64	15,380.70
Startup Cost (€)	175,572.11	175,572.11	-
CO_2 Emission from Generation (metric Tonnes)	45,200.89	44,961.73	239.15
CO_2 Emission from Startup (metric Tonnes)	574.14	574.14	-
CO_2 Emission from MWh (metric Tonnes/MWh)	0.51	0.51	1.09
April 13, 2011	Actual Load	TOU Load	Savings
Total Load (MWh)	94,502.02	94,309.54	192.48
System Generation Load (MWh)	73,061.55	72,869.07	192.48
Generation cost (€)	3,601,869.83	3,589,091.68	192.48
Startup Cost (€)	357,197.63	357,197.63	-
CO_2 Emission from Generation (metric Tonnes)	39047.01	38893.87	153.14
CO_2 Emission from Startup (metric Tonnes)	1,464.52	1,464.52	-
CO_2 Emission from MWh (metric Tonnes/MWh)	0.55	0.55	0.80
July 13, 2011	Actual Load	TOU Load	Savings
Total Load (MWh)	85,438.06	85,246.66	191.40
System Generation Load (MWh)	79,493.55	79,297.17	196.38
Generation cost (€)	3,587,483.67	3,577,943.98	9,548.69
Startup Cost (€)	24,168.60	24,168.60	-
CO_2 Emission from Generation (metric Tonnes)	36,145.60	35,989.31	156.29
CO_2 Emission from Startup (metric Tonnes)	94.51	94.51	-
CO_2 Emission from MWh (metric Tonnes/MWh)	0.46	0.46	0.80
October 12, 2011	Actual Load	TOU Load	Savings
Total Load (MWh)	98,614.94	98,383.8	231.77
System Generation Load (MWh)	89,606.92	89,375.15	231.77
Generation cost (€)	4,100,552.49	4,087,233.29	13,319.19
Startup Cost (€)	274,360.80	274,305.82	54.98
CO_2 Emission from Generation (metric Tonnes)	47,542.52	47,322.50	220.02
CO_2 Emission from Startup (metric Tonnes)	588.30	587.72	0.59
CO_2 Emission from MWh (metric Tonnes/MWh)	0.54	0.54	0.95

Table 4.2: Daily load, generation costs, and CO_2 emissions under actual load and time-of-use load

being out of service. January represents the winter months with the highest total load and July represents the summer months with the lowest total load.

The variable of interest is the ratio of CO_2 emissions reduced per MWh saved. Savings on January 12^{th} were 1.09 metric tonnes of CO_2 reduced per MWh saved. These results suggest that time of use pricing is most effective during winter months when baseload, mid-merit, and interconnector generation units are operating at maximum capacity. This demonstrates that reducing load from dirtier and more expensive peak units will result in larger emissions savings.

April 13 represents a weekday in the spring. Of the four samples, April 13 has the highest startup costs because mid-merit generators are scheduled to ramp up during the day to meet demand. A larger proportion of generation for coal units indicates that natural gas generation may be costlier on this day. Peak generation is mainly met with hydro and distillate generators, however, TOU simulation results indicate that the more expensive natural gas generation is reduced during peak hours resulting in lower emissions savings than if distillate generation were displaced.

Average weekdays in the summer, represented by July 13^{th}, have the lowest overall load and within day variation compared to other seasons. On days with low within day variation, fewer generators are required to ramp up and down resulting in lower startup costs and emissions. Figure 4.2(c) shows low wind generation compared to other months and natural gas generators are scheduled to meet the majority of the load. Simulated TOU peak and day reductions mainly impact coal and less efficient gas generation whereas increased usage during the night can be met by available Moyle units.

Figures 4.3(b) and 4.3(d) suggest weekdays during fall and spring months have similar load shapes but fall months with a more defined peak period met with gas and distillate units. October 12 shows an example of a day when interconnectors are offline and replaced by a mix of gas and coal fired units. These units are generally more expensive to operate and are dirtier emitted due to lower efficiency and type of fuel. As a result, CO_2 emissions per MWh generated may be higher than that of months when the interconnector is on. Unsurprisingly, 0.95 metric tonnes of CO_2 emissions per MWh saved is the second highest of the four days, suggesting TOU pricing is more efficient in reducing CO_2 emissions during the fall than in the spring and summer months.

Of the four days, there was one instance in the TOU simulation where the peak reductions allowed for a scheduled peaking generator to remain offline, resulting in start up and generation savings on this particular day. This suggests the potential for efficiency gains even with a TOU scheme with low estimated effects.

In the SEMO, the Moyle Interconnector is treated as a price-making unit and is subject to submitting daily bids in the market. The interconnector unit offers are relatively low cost (€20-30 per MW) and compete with cheaper gas and coal generation units on the merit curve to meet mid-merit generation needs. During the summer months when interconnection is not importing at maximum capacity, load shifting can displace gas and coal units with interconnector and hydro units. With the interconnector down in the fall of 2011, emission and cost of generation is expected to increase, as the island is required to ramp up more expensive generation units to meet the gap in demand.

4.6 Conclusion

Despite criticism of a low response to time of use pricing in the literature, I find evidence that suggests that even small reductions in peak and daily demand result in emissions and generation cost savings. TOU pricing appears to be the most effective in the winter and fall months when a larger proportion of peak demand is met with distillate and oil generation units. This policy is less effective over spring and summer months when the daily load is relatively flat without defined peak periods. The unique temperate region of Ireland makes this an interesting test case as we can see from the relatively flat daily loads shapes in the summer months. TOU pricing would have larger impacts if this particular fuel mix were located in regions with more variability in climate called for air conditioning. During these times, reducing daily load would result in lower emissions savings per kWh reduced. Often times, load shifting to the night time can be met with cleaner generation units from hydro and high efficiency gas units.

Still, the results in this chapter should be considered as optimistic as residential electricity consumption accounts for 30 percent of overall consumption in the Republic of Ireland. The Republic of Ireland consumes approximately 75 percent of electricity on the island. The TOU results imposed from the previous chapter assumes that The results in this chapter have significant policy implications for the future as demand for electricity continues to grow. Since 2011, installed wind capacity in the Republic of Ireland alone has almost doubled from 1631MW to 3015MW.[4] Coal and peat, the dirtiest of the fuels, continue to dominate a significant portion of the fuel mix in the generation market. As Ireland moves away from fossil fuel intensive generation and imported electricity, wind is expected to continue to fill in the gaps and phase out distillate and heavy fuel oil generation, emissions reductions will be determined primarily by natural gas and coal generators. Real time pricing may be a better policy alternative as it has been found to result in larger demand response than TOU pricing [13, 45].

[4] Installed wind capacity of 3015 MW in the Republic of Ireland is a 2015 figure from the Irish Wind Energy Association.

Appendix A: Appendix A

Figure A.1 shows the in-home display monitor provided through ESB Networks. The display home screen shows the following information:

1. Shows how household is doing compared to their pre-set daily budget,

2. Current price of electricity,

3. Cost of electricity has accumulated for the current month,

4. Price for each kWh of electricity at the peak, day, and night periods.

Figure A.1: In-home display monitor

	BM	M	IHD	Total
Did not receive payment	448	467	492	1,407
	56.28%	57.73%	61.42%	58.48%
Received payment	348	342	309	999
	43.72%	42.47%	38.58%	41.52%
Total	769	809	801	2,406

Note: Received payment means there was a positive balance of the trial, which was paid out to trial participants (See page 16).

Table A.1: Balancing credit payment: Percentage receiving payment by information treatment group

	Mean	Mean*	S.D.	Min.	Max.
BM	5.62	12.86	11.65	0	91.96
M	5.78	13.68	11.84	0	93.85
IHD	4.97	12.89	11.64	0	105.25

Note: Mean, S.D, Min., and Max. are descriptive statistics that include every household in the treatment group. Mean* is the average for those households who participated in the trial and received a payment at the end of it.

Table A.2: Summary of balancing credit payment (€): payment received by information treatment group

Appendix B: Appendix B

Fuel	t CO_2/TJ
Natural gas	56.9
Gas/diesel/distillate oil	73.3
Residual oil	76.0
Coal	94.6
Milled Peat	116.7

Table B.1: Fuel and CO_2 conversion factors

ID	Unit Name	IE/ NI	Cycle	Start Fuel	Fuel for Generation and No Load	Min Stable Capacity	Max capacity	No Load Heat Requirement (GJ/hr)	Capacity Point [MW exported]				Incremental Heat Rate Slope [GJ/MWhr]			
AD1	Aghada Unit 1	IE	CSC	Gas	Gas	35.0	258.0	188.15	35	120	190	258	8.03	8.03	8.70	8.77
ADC	Aghada CCGT	IE	CCGT	Gas	Gas	215.0	431.6	354.51	215	432	-	-	5.50	5.50	-	-
AT4	Aghada CT Unit 4	IE	OCGT	Gas	Gas	15.0	90.0	285.30	15	40	90	-	7.83	7.83	9.72	-
DB1	Dublin Bay Power	IE	CCGT	Gas	Gas	207.0	415.0	479.34	207	415	-	-	5.16	5.16	-	-
HN2	Huntstown Phase II	IE	CCGT	Gas	Gas	194.0	404.0	603.60	195	230	412	-	4.24	5.62	5.74	-
HNC	Huntstown	IE	CCGT	Gas	Gas	200.0	343.0	541.20	200	230	250	352	4.46	5.19	5.99	6.01
MRC No ST	Marina No ST	IE	OCGT	Gas	Gas	20.0	85.0	257.13	47	81	85	-	8.66	9.48	11.41	-
PBC	Poolbeg Combined Cycle	IE	CCGT	Gas	Gas	232.0	480.0	426.19	232	480	-	-	6.26	6.26	-	-
SK3	Sealrock 3	IE	OCGT	Gas	Gas	40.0	83.0	100.00	40	83	-	-	5.00	5.00	-	-
SK4	Sealrock 4	IE	OCGT	Gas	Gas	40.0	83.0	100.00	40	83	-	-	5.00	5.00	-	-
TY	Tynagh	IE	CCGT	Gas	Gas	196.0	388.5	584.00	196	388	-	-	5.09	5.09	-	-
WG	Whitegate	IE	CCGT	Gas	Gas	222.5	445.0	680.00	223	224	445	-	4.72	4.72	4.98	-
GI1	Great Island Unit 1	IE	CSC	61% Oil, 39% Distillate	Oil	25.0	54.0	51.07	25	45	54	-	13.59	13.59	13.67	-
GI2	Great Island Unit 2	IE	CSC	61% Oil, 39% Distillate	Oil	25.0	49.0	51.07	25	45	49	-	13.59	13.59	13.67	-
GI3	Great Island Unit 3	IE	CSC	61% Oil, 39% Distillate	Oil	30.0	109.0	102.65	30	98	109	-	10.88	10.88	10.98	-
TB1	Tarbert Unit 1	IE	CSC	61% Oil, 39% Distillate	Oil	20.0	54.0	44.66	18	46	54	-	11.63	11.63	11.75	-
TB2	Tarbert Unit 2	IE	CSC	61% Oil, 39% Distillate	Oil	20.0	54.0	44.66	18	46	54	-	11.63	11.63	11.75	-
TB3	Tarbert Unit 3	IE	CSC	70% Oil, 30% Distillate	Oil	34.9	240.0	247.61	35	100	180	240	8.07	8.07	9.06	9.15
TB4	Tarbert Unit 4	IE	CSC	70% Oil, 30% Distillate	Oil	34.9	240.0	247.62	35	120	190	241	8.40	8.40	9.43	9.64
MP1	Moneypoint Unit 1	IE	CSC	68% Coal, 32% GasOil	Coal	136.0	280.0	173.41	128	195	280	-	9.46	9.46	9.56	-
MP2	Moneypoint Unit 2	IE	CSC	68% Coal, 32% GasOil	Coal	136.0	280.0	173.41	128	195	280	-	9.46	9.46	9.56	-
MP3	Moneypoint Unit 3	IE	CSC	68% Coal, 32% GasOil	Coal	136.0	280.0	173.41	128	195	280	-	9.46	9.46	9.56	-
ED1	Edenderry	IE	CSC	Oil	Peat/Biomass	41.0	117.6	497.60	88	112	118	-	3.93	8.95	8.95	-
LR4	Lough Rea	IE	CSC	Peat	Peat	73.0	91.0	84.10	73	91	-	-	8.53	8.53	-	-
WO4	West Offaly Power	IE	CSC	Peat	Peat	106.2	137.0	114.71	106	137	-	-	8.24	8.24	-	-
AA1	Ardnacrusha Unit 1	IE	Hydro	Hydro		11.9	21.0	-	-	-	-	-	-	-	-	-
AA2	Ardnacrusha Unit 2	IE	Hydro	Hydro		11.9	22.0	-	-	-	-	-	-	-	-	-
AA3	Ardnacrusha Unit 3	IE	Hydro	Hydro		11.9	19.0	-	-	-	-	-	-	-	-	-
AA4	Ardnacrusha Unit 4	IE	Hydro	Hydro		11.9	24.0	-	-	-	-	-	-	-	-	-
ER1	Erne Unit 1	IE	Hydro	Hydro		4.0	10.0	-	-	-	-	-	-	-	-	-
ER2	Erne Unit 2	IE	Hydro	Hydro		4.0	10.0	-	-	-	-	-	-	-	-	-
ER3	Erne Unit 3	IE	Hydro	Hydro		5.0	22.5	-	-	-	-	-	-	-	-	-
ER4	Erne Unit 4	IE	Hydro	Hydro		5.0	22.5	-	-	-	-	-	-	-	-	-
LE1	Lee Unit 1	IE	Hydro	Hydro		3.0	15.0	-	-	-	-	-	-	-	-	-
LE2	Lee Unit 2	IE	Hydro	Hydro		1.0	4.0	-	-	-	-	-	-	-	-	-
LE3	Lee Unit 3	IE	Hydro	Hydro		3.0	8.0	-	-	-	-	-	-	-	-	-
LI1	Liffey Unit 1	IE	Hydro	Hydro		3.0	15.0	-	-	-	-	-	-	-	-	-
LI2	Liffey Unit 2	IE	Hydro	Hydro		3.0	15.0	-	-	-	-	-	-	-	-	-
LI4	Liffey Unit 4	IE	Hydro	Hydro		4.0	4.0	-	-	-	-	-	-	-	-	-
LI5	Liffey Unit 5	IE	Hydro	Hydro		0.2	4.0	-	-	-	-	-	-	-	-	-
TH1	Turlough Hill Unit 1	IE	Pumped Storage	Pumped Storage		5.0	73.0	0.00	-	-	-	-	-	-	-	-
TH2	Turlough Hill Unit 2	IE	Pumped Storage	Pumped Storage		5.0	73.0	0.00	-	-	-	-	-	-	-	-
TH3	Turlough Hill Unit 3	IE	Pumped Storage	Pumped Storage		5.0	73.0	0.00	-	-	-	-	-	-	-	-
TH4	Turlough Hill Unit 4	IE	Pumped Storage	Pumped Storage		5.0	73.0	0.00	-	-	-	-	-	-	-	-
AT1	Aghada CT Unit 1	IE	OCGT	Gas	Gas	15.0	88.0	285.30	15	40	90	-	7.83	7.83	9.72	-
AT2	Aghada CT Unit 2	IE	OCGT	Gas	Gas	15.0	90.0	285.30	15	40	90	-	7.83	7.83	9.72	-
ED3	Cushaling	IE	OCGT	Distillate	Distillate	5.0	56.0	85.00	56	-	-	-	9.00	-	-	-
ED5	Cushaling	IE	OCGT	Distillate	Distillate	5.0	56.0	85.00	56	-	-	-	9.00	-	-	-
NW5	Northwall Unit 5	IE	OCGT	Distillate	Distillate	5.0	104.0	310.93	5	104	-	-	9.76	9.76	-	-
RH1	Rhode 1	IE	OCGT	Distillate	Distillate	5.0	52.0	85.01	5	52	-	-	9.82	9.82	-	-
RH2	Rhode 2	IE	OCGT	Distillate	Distillate	5.0	52.0	85.01	5	52	-	-	9.82	9.82	-	-
TP1	Tawnaghmore 1	IE	OCGT	Distillate	Distillate	5.0	52.0	86.62	5	52	-	-	9.59	9.59	-	-
TP3	Tawnaghmore 3	IE	OCGT	Distillate	Distillate	5.0	52.0	86.62	5	52	-	-	9.59	9.59	-	-
B10	Ballylumford Unit 10	NI	CCGT	Gas	Gas	63.0	101.0	88.34	63	101	-	-	6.00	6.00	-	-
B31	Ballylumford CCGT Unit 31	NI	CCGT	Gas	Gas	113.0	247.0	280.80	113	247	-	-	5.94	5.94	-	-
B32	Ballylumford Unit 32	NI	CCGT	Gas	Gas	113.0	247.0	280.80	113	247	-	-	5.94	5.94	-	-
B4	Ballylumford Unit 4	NI	CSC	Gas	Gas	54.0	170.0	166.50	54	170	-	-	9.72	9.72	-	-
B5	Ballylumford Unit 5	NI	CSC	Gas	Gas	54.0	170.0	166.50	54	170	-	-	10.20	10.20	-	-
B6	Ballylumford Unit 6	NI	CSC	Gas	Gas	54.0	170.0	166.50	54	170	-	-	10.00	10.00	-	-
Contour 1	Contour Global unit 1	NI	CHP	Gas	Gas	1.5	3.0	2.45	3	-	-	-	7.35	-	-	-
Contour 2	Contour Global unit 2	NI	CHP	Gas	Gas	1.5	3.0	2.54	3	-	-	-	7.35	-	-	-
CPS CCGT	Coolkeeragh CCGT	NI	CCGT	Gas	Gas	260.0	425.0	624.51	260	328	372	425	4.32	5.26	5.49	5.52
K1 Coal 220	Kilroot Unit 1 FGD	NI	CSC	Oil	Coal	54.0	238.0	272.45	54	175	198	238	8.87	8.87	8.87	28.26
K2 Coal 220	Kilroot Unit 2 FGD	NI	CSC	Oil	Coal	54.0	238.0	272.45	54	175	198	238	8.87	8.87	8.87	28.26
BGT1	Ballylumford GT1	NI	OCGT	Distillate	Distillate	8.0	58.0	171.00	8	53	58	-	10.50	10.50	10.50	-
BGT2	Ballylumford GT2	NI	OCGT	Distillate	Distillate	8.0	58.0	171.00	8	53	58	-	10.50	10.50	10.50	-
CGT8	Coolkeeragh GT8	NI	OCGT	Distillate	Distillate	8.0	58.0	171.00	8	58	-	-	10.50	10.50	-	-
KGT1	Kilroot GT1	NI	OCGT	Distillate	Distillate	5.4	29.0	97.38	5	24	29	-	10.50	10.50	10.50	-
KGT2	Kilroot GT2	NI	OCGT	Distillate	Distillate	5.4	29.0	97.38	5	24	29	-	10.50	10.50	10.50	-
KGT3	Kilroot GT3	NI	OCGT	Distillate	Distillate	12.8	41.6	115.39	13	42	-	-	9.24	9.24	-	-
KGT4	Kilroot GT4	NI	OCGT	Distillate	Distillate	12.8	41.6	115.39	13	42	-	-	9.24	9.24	-	-
Contour 3	Contour Global unit 3	NI	CHP	Gas	Gas	1.5	3.0	2.54	3	-	-	-	7.35	-	-	-

Note: OCGT= open cycle gas turbine, CSC = condense steam cycle, CHP = combined heat and power, Pumped Storage = pumped storage hydro. Source: Commission for Energy Regulation All Island Project.

Figure B.1: Generation unit cycle, fuel, and heat rate parameters

ID	Unit Name	Forced Outage Rate,%	Mean Time to Repair, hrs	Ramp Rate Up, MW/min	Ramp Rate Down, MW/min	Min Up Time (hrs)	Min Down Time (hrs)	Start up Energy (GJ) Cold	Start up Energy (GJ) Warm	Start up Energy (GJ) Hot	Hot to Warm, hrs	Warm to Cold, hrs
AD1	Aghada Unit 1	6.3%	50	3.4	3.7	4.00	3.50	4302	2185	1273	5	72
ADC	Aghada CCGT	2.9%	50	22.0	22.0	4.00	4.00	2400	1800	1200	12	72
AT4	Aghada CT Unit 4	4.8%	50	5.0	5.0	0.00	0.75	63	63	63	12	60
DB1	Dublin Bay Power	2.0%	24	10.0	9.0	4.00	0.00	7700	2604	2600	1	72
HN2	Huntstown Phase II	7.0%	55	20.0	20.0	4.00	4.00	644	531	318	12	60
HNC	Huntstown	7.0%	55	7.0	7.0	4.00	4.00	4772	2803	835	12	60
MRC No ST	Marina No ST	4.8%	50	5.0	5.0	1.00	0.50	63	63	63	12	120
PBC	Poolbeg Combined Cycle	5.9%	50	16.5	16.5	4.00	4.00	2800	1800	1500	8	120
SK3	Sealrock 3 (Aughinish CHP)	3.0%	33	6.0	6.0	4.00	4.00	1200	1000	800	8	24
SK4	Sealrock 4 (Aughinish CHP)	3.0%	33	6.0	6.0	4.00	4.00	1200	1000	800	8	24
TY	Tynagh	3.6%	55	15.0	15.0	4.00	4.00	4115	2954	1900	8	40
WG	Whitegate	3.4%	32.14	30.0	30.0	4.00	4.00	333	310	277	12	72
GI1	Great Island Unit 1	0.2%	50	1.0	1.0	4.00	2.00	562	449	218	12	48
GI2	Great Island Unit 2	8.6%	50	1.0	1.0	4.00	2.00	562	449	218	12	48
GI3	Great Island Unit 3	1.7%	50	0.6	1.5	4.00	4.00	743	600	293	12	60
TB1	Tarbert Unit 1	0.3%	50	1.0	1.0	2.00	2.00	562	449	218	12	60
TB2	Tarbert Unit 2	1.1%	50	1.0	1.0	2.00	2.00	562	449	218	12	60
TB3	Tarbert Unit 3	0.3%	50	2.8	2.2	24.00	4.00	3180	1934	1072	14	120
TB4	Tarbert Unit 4	5.0%	50	2.8	2.2	24.00	4.00	3180	1934	1072	14	120
MP1	Moneypoint Unit 1 FGD SCR	6.3%	50	1.4	5.0	6.00	5.00	14620	6920	4360	12	72
MP2	Moneypoint Unit 2 FGD SCR	5.9%	50	1.4	5.0	6.00	5.00	14620	6920	4360	12	72
MP3	Moneypoint Unit 3 FGD SCR	6.1%	50	1.4	5.0	6.00	5.00	14620	6920	4360	12	72
ED1	Edenderry	4.0%	72	1.8	1.8	4.00	0.50	2308	1084	436	4	48
LR4	Lough Rea	5.0%	50	1.5	1.5	4.00	4.00	500	400	300	12	60
WO4	West Offaly Power	7.1%	50	1.5	1.5	4.00	4.00	750	600	450	12	60
AA1	Ardnacrusha Unit 1	2.4%	60	6.0	6.0	0.00	0.25	0	0	0	12	60
AA2	Ardnacrusha Unit 2	2.4%	60	6.0	6.0	0.00	0.25	0	0	0	12	60
AA3	Ardnacrusha Unit 3	2.4%	60	6.0	6.0	0.00	0.25	0	0	0	12	60
AA4	Ardnacrusha Unit 4	2.3%	60	6.0	6.0	0.00	0.25	0	0	0	12	60
ER1	Erne Unit 1	2.4%	60	5.0	10.0	0.00	0.17	0	0	0	12	60
ER2	Erne Unit 2	2.4%	60	5.0	10.0	0.00	0.17	0	0	0	12	60
ER3	Erne Unit 3	2.4%	60	10.0	22.5	0.00	0.17	0	0	0	12	60
ER4	Erne Unit 4	0.9%	60	10.0	22.5	0.00	0.17	0	0	0	12	60
LE1	Lee Unit 1	2.3%	60	2.4	15.0	0.00	0.17	0	0	0	12	60
LE2	Lee Unit 2	2.3%	60	1.5	4.0	0.00	0.17	0	0	0	12	60
LE3	Lee Unit 3	2.3%	60	0.6	8.0	0.00	0.17	0	0	0	12	60
LI1	Liffey Unit 1	2.5%	60	5.0	10.0	0.00	0.20	0	0	0	12	60
LI2	Liffey Unit 2	2.3%	60	5.0	10.0	0.00	0.20	0	0	0	12	60
LI4	Liffey Unit 4	2.5%	60	2.0	2.0	0.25	0.13	0	0	0	12	60
LI5	Liffey Unit 5	2.5%	60	0.0	2.0	0.00	0.12	0	0	0	12	60
TH1	Turlough Hill Unit 1	6.4%	60	210.0	270.0	0.00	0.00	0	0	0	12	60
TH2	Turlough Hill Unit 2	2.1%	60	210.0	270.0	0.00	0.00	0	0	0	12	60
TH3	Turlough Hill Unit 3	6.4%	60	210.0	270.0	0.00	0.00	0	0	0	12	60
TH4	Turlough Hill Unit 4	6.4%	60	210.0	270.0	0.00	0.00	0	0	0	12	60
AT1	Aghada CT Unit 1	4.9%	50	5.0	5.0	0.00	0.75	63	63	63	12	60
AT2	Aghada CT Unit 2	4.9%	50	5.0	5.0	0.00	0.75	63	63	63	12	60
ED3	Cushaling	2.0%	24	5.0	5.0	0.00	0.08	20	20	20	0.5	1
ED5	Cushaling	2.0%	24	5.0	5.0	0.00	0.08	20	20	20	0.5	1
NW5	Northwall Unit 5	4.4%	50	8.0	8.0	0.00	0.50	50	50	50	12	60
RH1	Rhode 1	0.0%	50	5.0	10.0	0.00	0.75	24	24	24	12	60
RH2	Rhode 2	0.2%	50	5.0	10.0	0.00	0.75	24	24	24	12	60
TP1	Tawnaghmore 1	1.3%	50	5.0	10.0	0.00	0.75	24	24	24	12	60
TP3	Tawnaghmore 3	0.3%	50	5.0	10.0	0.00	0.75	24	24	24	12	60
B10	Ballylumford Unit 10	5.0%	72	1.1	4.0	0.02	0.25	405	225	135	8	40
B31	Ballylumford CCGT Unit 31	4.0%	72	3.1	11.0	0.02	0.25	1611	666	567	8	40
B32	Ballylumford Unit 32	4.0%	72	3.1	11.0	0.02	0.25	1611	666	567	8	40
B4	Ballylumford Unit 4	8.0%	72	2.0	9.7	0.02	0.02	2070	1530	810	10	26
B5	Ballylumford Unit 5	8.0%	72	2.0	9.8	0.02	0.02	2070	1530	810	10	26
B6	Ballylumford Unit 6	8.0%	72	2.0	9.8	0.02	0.02	2070	1530	810	10	26
Contour 1	Contour Global unit 1	4.0%	60	0.8	0.8	0.17	0.25	-	-	-	0.25	0.25
Contour 2	Contour Global unit 2	4.0%	60	0.8	0.8	0.17	0.25	-	-	-	0.25	0.25
CPS CCGT	Coolkeeragh CCGT	3.0%	72	8.0	18.5	4.00	4.00	5220	3024	1080	8	36
K1 Coal 220	Kilroot Unit 1 FGD	3.2%	72	4.6	5.8	4.00	0.02	2152	1580	941	10	55
K2 Coal 220	Kilroot Unit 2 FGD	3.2%	72	4.6	5.8	4.00	0.02	2152	1580	941	10	55
BGT1	Ballylumford GT1	1.4%	72	10.0	18.0	0.02	0.25	8	8	8	n/a = OCGT	0
BGT2	Ballylumford GT2	1.4%	72	10.0	18.0	0.02	0.25	8	8	8	n/a = OCGT	0
CGT8	Coolkeeragh GT8	1.1%	72	10.0	10.0	0.02	0.25	8	8	8	n/a = OCGT	0
KGT1	Kilroot GT1	0.8%	72	6.0	6.0	0.33	0.25	8	8	8	n/a = OCGT	0
KGT2	Kilroot GT2	0.8%	72	6.0	6.0	0.33	0.25	8	8	8	n/a = OCGT	0
KGT3	Kilroot GT3	2.0%	72	10.0	10.0	0.33	0.38	10	10	10	n/a = OCGT	0
KGT4	Kilroot GT4	2.0%	72	10.0	10.0	0.33	0.38	10	10	10	n/a = OCGT	0
Contour 3	Contour Global unit 3	4.0%	60	0.8	0.8	0.17	0.25	-	-	-	0.25	0.25

Source: Commission for Energy Regulation All Island Project.

Figure B.2: Generation unit operation parameters

Bibliography

[1] "Census 2011 Profile 5 Households and Families - Living Arrangements in Ireland - CSO - Central Statistics Office." Accessed January 22, 2016. http://www.cso.ie/en/census/census2011reports/census2011profile5householdsandfamilies-livingarrangementsinireland/

[2] "Electricity Services in Ireland", n.d. Online. Internet. 8 Oct. 2013. Available online: http://www.citizensinformation.ie/en/consumer_affairs/energy_and_water_services/electricity_services_in_ireland.html

[3] "National Electric Transmission Congestion Studies." U.S. Department of Energy (DOE). n.d. Online. Internet 21 Oct. 2013. Available: http://energy.gov/oe/services/electricity-policy-coordination-and-implementation/transmission-planning/national.

[4] ACEEE. "Energy Efficiency Programs." Accessed October 2, 2015. http://aceee.org/portal/programs.

[5] Albadi, M.H., and El-Saadany, E.F. (2008). "A summary of demand response in electricity markets." *Electric Power Systems*, 78, 1989-1996.

[6] Alberini, A., Gans, W., and Towe, C. (2016). "Free Riding, Upsizing, and Energy Efficiency Incentives in Maryland Homes." *The Energy Journal*, 37(1), 259-290.

[7] Allcott, H. (2011). "Rethinking real-time electricity pricing." *Resource and Energy Economics*, 33(4): 820842. http://dx.doi.org/10.1016/j.reseneeco.2011.06.003.

[8] Allcott, H., and Rogers, T. (2014). "The Short-Run and Long-Run Effects of Behavioral Interventions? Experimental Evidence from Energy Conservation." *American Economic Review*, 204(10): 3003-3037.

[9] Anderson, W., and White, V. (2009). "Exploring consumer preferences for home energy display functionality: A report for the Energy Saving Trust." Bristol, Center for Sustainable Energy.

[10] Ater, I., and Landsman, V. (2013). "Do Customers Learn from Experience? Evidence from Retail Banking." *Management Science*, 59(9), 2019-2035.

[11] Baladi, S. M. (1998). "Residential response to voluntary time-of-use electricity rates." *Resource and Energy Economics*, 20(3), 225-244. doi:10.1016/S0928-7655(97)00025-0

[12] Bartusch, C., Wallin, F., Odlare, M., Vassileva, I., and Wester, L. (2011). "Introducing a demand-based electricity distribution tariff in the residential sector: Demand response and customer perception." *Energy Policy*, 39, 5008-5025.

[13] Borenstein, S. (2005). "The Long-Run Efficiency of Real-Time Electricity Pricing." *The Energy Journal*, 26 (3).

[14] Brounen, D., Kok, N., and Quigley, J. M. (2013). "Energy literacy, awareness, and conservation behavior of residential households." *Energy Economics*, 38, 42-50. doi:10.1016/j.eneco.2013.02.008

[15] Canay, I.A. (2011). "A Simple Approach to Quantile Regression for Panel Data." *The Econometrics Journal*, 14(3), 368-386.

[16] Carroll, J., Lyons, S., and Denny, E. (2014). "Reducing household electricity demand through smart metering? The role of improved information about energy saving." *Energy Economics*, 45, 234243. doi:10.1016/j.eneco.2014.07.007

[17] Clancy, M. and Gaffney, F. (2014). "Quantifying Irelands Fuel and CO2 Emissions Savings from Renewable Electricity in 2012." SEAI. May 2014. Online. 6 July 2014. Available: http://www.seai.ie/Publications/Statistics_Publications/Energy_Modelling_Group_Publications/Quantifying-Ireland's-Fuel-and-CO2-Emissions-Savings-from-Renewable-Electricity-in-2012.pdf

[18] Commission for Energy Regulation (2011). CER Factsheets on the Single Electricity Market. Online. Internet. 6 July 2014. Available online: http://www.cer.ie/docs/000262/cer11075.pdf

[19] Caves, D., Christensen, L., and Herriges, J. (1984). “The consistency of the residential customer response in time-of-use electricity pricing experiments.” *Journal of Econometrics*, 26, 179-203.

[20] Commission for Energy Regulation (2011). Electricity Smart Metering Customer Behaviour Trials (CBT) Findings Report (CER/11/080a). Available online: http://www.cer.ie/en/information-centre-reports-and-publications.aspx?article=5dd4bce4-ebd8-475e-b78d-da24e4ff7339

[21] Cotter, N., Monahan, E., McAvoy, H., and Goodman, P. (2012). “Coping with the cold exploring relationships between cold housing, health and social wellbeing in a sample of older people in Ireland.” *Quality in Ageing and Older Adults*, 13 (1), 38 47.

[22] Darby, S. (2006). “The Effectiveness of Feedback on Energy Consumption.” A Review for DEFRA of the Literature on Metering, Billing and Direct Displays, Environmental Change Institute, University of Oxford, Oxford. Available online: http://www.defra.gov.uk/environment/energy/research/

[23] Darby, S. (2010). “Smart metering: what potential for householder engagement?” *Building Research and Information*, 38(5), 442457. doi:10.1080/09613218.2010.492660

[24] Davis, M. (2011). “Behavior and energy savings evidence from a series of experimental interventions.” Technical report, Environmental Defense Fund.

[25] Di Cosmo, V. and Valeri, L. M. (2014). “The Effect of Wind on Electricity CO2 Emissions: The Case of Ireland.” ESRI Working Paper No. 493.

[26] Di Cosmo, V., Lyons, S., and Nolan, A. (2014). “Estimating the Impact of TOU Pricing on Irish Electricity Demand.” *The Energy Journal*, 35(2). doi:10.5547/01956574.35.2.6

[27] Dimitropoulos, J. (2007). “Appraisal of Costs and Benefits of Smart Meter Roll Out Options.” BERR. Available: http://webarchive.nationalarchives.gov.uk/+/http:/www.berr.gov.uk/files/file45997.pdf

[28] Ehrhardt-Martinez, K., Donnelly, K.A., and Laitner, J. A. (2010). “Advanced Metering Initiatives and Feedback Programs: A Meta-Review for Household

Electricity-Saving Opportunities." American Council for an Energy-Efficient Economy, Report No. E105 Enerdata/ World Energy Council. Energy Efficiency Indicators. Available: https://www.wec-indicators.enerdata.eu/household-electricity-use.html

[29] Environmental Protection Agency (EPA). "Ireland's Greenhouse Gas Emissions in 2012." 15 Apr. 2014. Online. 6 July 2014. Available: http://www.epa.ie/pubs/reports/air/airemissions/GHG_1990-2012_April_2014.pdf

[30] Faruqui, A., Harris, D., and Hledik, R. (2010). "Unlocking the 53 billion Euro savings from smart meters in the EU: How increasing the adoption of dynamic tariffs could make or break the EUs smart grid investment." *Energy Policy*, 38(10), 6222-6231. doi:10.1016/j.enpol.2010.06.010

[31] Faruqui, A., Sergici, S., and Sharif, A. (2010). "The impact of informational feedback on energy consumption- A survey of the experimental evidence." *Energy*, 35(4), 1598-1608. doi:10.1016/j.energy.2009.07.042

[32] Filippini, M. (1995). "Swiss residential demand for electricity by time-of-use." *Resource and Energy Economics*, 17, 281-290.

[33] Filippini, M. (1995). "Swiss Residential Demand for Electricity by Time-of-Use: An Application of the Almost Ideal Demand System." *The Energy Journal*, 16(1), 27-39.

[34] Filippini, M. (2011). "Short- and long-run time-of-use price elasticities in Swiss residential electricity demand." *Energy Policy*, 39(10), 5811-5817. doi:10.1016/j.enpol.2011.06.002

[35] Fischer, C. (2008). "Feedback on household electricity consumption: a tool for saving energy?" *Energy Efficiency*, 1(1), 79-104.doi:10.1007/s12053-008-9009-7

[36] Gans, W., Alberini, A., and Longo, A. (2013). "Smart meter devices and the effect of feedback on residential electricity consumption: Evidence from a natural experiment in Northern Ireland." *Energy Economics*, 36, 729743. doi:10.1016/j.eneco.2012.11.022

[37] Gerpott, T. J., and Paukert, M. (2013). "Determinants of willingness to pay for smart meters: An empirical analysis of household customers in Germany." *Energy Policy*, 61, 483495. doi:10.1016/j.enpol.2013.06.012

[38] Gilbert, B., and Graff Zivin, J. (2014). "Dynamic salience with intermittent billing: Evidence from smart electricity meters." *Journal of Economic Behavior and Organization*, 107, 176190. doi:10.1016/j.jebo.2014.03.011

[39] Grønhøj, A., and Thøgersen, J. (2011). "Feedback on household electricity consumption: Learning and social influence processes." *International Journal of Consumer Studies*, 35, 138145. doi:10.1111/j.1470-6431.2010.00967.x

[40] Hargreaves, T., Nye, M., and Burgess, J. (2013). "Keeping energy visible? Exploring how householders interact with feedback from smart energy monitors in the longer term." *Energy Policy*, 52, 126-134. doi:10.1016/j.enpol.2012.03.027

[41] Healy, J. (2003). "Do fuel-poor households exhibit higher risk factors associated with poor health?" *International Journal of Health Promotion and Education*, 41 (1), 14-20. Doi: 10.1080/14635240.2003.10806214

[42] Healy, J.D., and Clinch, J. P. (2002). "Fuel poverty, thermal comfort and occupancy: results of a national household-survey in Ireland." *Applied Energy*, 73, 329-343.

[43] Herter, K. (2007) "Residential implementation of critical-peak pricing of electricity." *Energy Policy*, 35(4), 2121-2130.

[44] Hill et al. 1983 ch2

[45] Holland, S. P. and Mansur, E. T. (2006). "The Short-Run Effects of Time-Varying Prices in Competitive Electricity Markets." *The Energy Journal*, 27 (4), 127-155.

[46] Holland, S. P. and Mansur, E. T. (2008). "Is Real-Time Pricing Green? The Environmental Impacts of Electricity Demand Variance." *The Review of Economics and Statistics*, 90(3), 550-561.

[47] Houde, S., Todd, A., Sudarshan, A., Flora, J. A., and Armep, K. C. (2013). "Real-time Feedback and Electricity Consumption?: A Field Experiment Assessing the Potential for Savings and Persistence." *The Energy Journal*, 34(1), 87103.

[48] Howley, M., Dennehy, E., O Gallachoir, B., and Holland M. (2013). "Energy in Ireland 1990-2011." Sustainable Energy Authority of Ireland.

[49] Iacus, S. M., King, G., and Porro, G. (2011). "Causal inference with balance checking: coarsened exact matching." *Political Analysis*, 15, 199-236.

[50] Iacus, S., Blackwell, M., King, G., and Porro, G. (2009). "cem: Coarsened exact matching in Stata." *The Stata Journal,* 9(4), 524-546. Ito, K. (2010). "Do

Consumers Respond to Average or Marginal Prices? Evidence from Nonlinear Electricity Pricing." Available at: http://ei.haas.berkeley.edu/pdf/working_papers/WP210.pdf.

[51] Ito, K., Ida, T., and Tanaka, M. (2013). "Using Dynamic Electricity Pricing to Address Energy Crises: Evidence from Randomized Field Experiments." 36th Annual NBER Summer Institute, Cambridge, MA, USA. Available: http://www.econ.kyoto-u.ac.jp/~ida/4Hoka/smagri/20133023Ito_Ida_Tanaka_Dynamic_Pricing.pdf

[52] Ivanov, C., Getachew, L., Fenrick, S.A., and Vittetoe, B. (2013). "Enabling technologies and energy savings: The case of EnergyWise Smart Meter Pilot of Connexus Energy." *Utilities Policy*, 26, 7684. doi:10.1016/j.jup.2012.10.001

[53] Jessoe, K., and Rapson, D. (2014). "Knowledge is (Less) Power: Experimental Evidence from Residential Energy Use." *American Economic Review, 104 (4), 1417-1438*.

[54] Joachain, H., and Klopfert, F. (2014). "Smarter than metering? Coupling smart meters and complementary currencies to reinforce the motivation of households for energy savings." *Ecological Economics*, 105, 89-96. doi:10.1016/j.ecolecon.2014.05.017

[55] Kohler and Mitchel 1984 ch2

[56] Madlener, R., Rosen, C., Päivärinta, J., and Harmsen-van Hout, M.J.W. (2014). "Subannual Billing Information for Heating and Water Costs." FCN Project Study on behalf of Arbeitsgemeinschaft Heiz- und Wasserkostenverteilung e.V. (Heiwako), Bonn, February.

[57] Matsukawa, I. (2000). "Household Response to Incentive Payments for Load Shifting: A Japanese Time-of-Day Electricity Pricing Experiment." *The Energy Journal*, 21(1), 73-86.

[58] Matsukawa, I. (2001). "Household Response to Optional Peak-Load Pricing of Electricity." Journal of Regulatory Economics, 20(3), 249-267.

[59] Miravete, E. J. (2003). "Choosing the Wrong Calling Plan? Ignorance and Learning." *The American Economic Review*, 93(1), 297-310.

[60] Morse, D. L., Coulter, M.P., Nazarian, L. F., and Napodano, R. J. (1981). "Waning Effectiveness of Mailed Reminders on Reducing Broken Appointments." *Pediatrics*, 48 (6), 846-849.

[61] Narayanan, S., Chintagunta, P. K., and Miravete, E. J. (2007). "The role of self-selection, usage uncertainty, and learning in the demand for local telephone service." *Quantitative Marketing and Economics*, 5 (1), 1-34.

[62] Newsham, G. R., and Bowker, B. G. (2010). "The effect of utility time-varying pricing and load control strategies on residential summer peak electricity use: A review." *Energy Policy*, 38(7), 3289-3296. doi:10.1016/j.enpol.2010.01.027

[63] Office of Energy Efficiency and Renewable Energy. (2015) "Appliance and Equipment Standards Fact Sheet." Available: http://energy.gov/eere/buildings/downloads/appliance-and-equipment-standards-fact-sheet.

[64] Pepco. (2013). Potomac Electric Power Companys Distribute of Columbia Dynamic Pricing Program Proposal (Formal Case No. 1083 and 1086). Available online: http://www.pepco.com/uploadedFiles/wwwpepcocom/1083-1086-Pepco's-DC-Dynamic-Pricing-Program-Proposal.pdf

[65] Richins, M. L. and Bloch, P. H. (1986). "After the New Wears Off: The Temporal Context of Product Involvement." *Journal of Consumer Research*, 13, 280-285.

[66] Richins, M. L. and Bloch, P. H. (1991). "Post-purchase product satisfaction: Incorporating the effects of involvement and time." *Journal of Business Research*, 23 (2), 145-158.

[67] Selwyn, N. (2004). "The information aged: A qualitative study of older adults use of information and communications technology." *Journal of Aging Studies*, 18, 369-384.

[68] Sexton, R. J., Brown J., N., and Konakayama, A. (1987). "Consumer response to continuous-display electricity-use monitors in a time-of-use pricing experiment." *Journal of Consumer Research*, 14, 5562.

[69] Sexton, R. J., Sexton, T. A., Wann, J. J., and Kling, C. L. (1989). "The Conservation and Welfare Effects of Information in a Time-of-Day Pricing Experiment." *Land Economics*, 65(3), 272-279.

[70] Sexton, S. (2011). "DRAFT: Automatic Bill Payment, Price Salience, and Consumption: Evidence from Residential Electricity Consumption", 114. Retrieved from http://ecnr.berkeley.edu/vfs/PPs/Sexton-Ste/web/ABP.pdf.

[71] Stango, V., and Zinman, J. (2011). "Limited and varying consumer attention: evidence from shocks to the salience of bank overdraft fees." NBER Working PaperNo. 17028, National Bureau of Economic Research.

[72] Sustainable Energy Authority of Ireland (SEAI). (2013) "Energy in the Residential Sector 2013 Report." SEAI Online. 16 Oct. 2013. Available: http://www.seai.ie/Publications/Statistics_Publications/EPSSU_Publications/Energy-in-the-Residential-Sector-2013.pdf.

[73] Torriti, J. (2012). "Price-based demand side management: Assessing the impacts of TOU tariffs on residential electricity demand and peak shifting in Northern Italy." *Energy*, 44 (1), 576583. doi:10.1016/j.energy.2012.05.043

[74] Tuohy, A., Bazilian, M., Doherty, R., O Gallachoir, B., and OMalley, Mark. (2009) "Burning Peat in Ireland: and electricity market dispatch perspective." *Energy Policy*, 37(8), 3035-3042.

[75] UK Department of Energy and Climate Change (2014). "Quarterly Energy Prices." National Statistics. Available: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/322799/qep_June_2014.pdf.

[76] Weare, C. (2003). The California Electricity Crisis: Causes and Policy Options. San Francisco, Public Policy Institute of California.

[77] Wichman, C.J. (2015). Information and Environmental Policy (Doctoral Dissertation). Retrieved from http://drum.lib.umd.edu/handle/1903/16564.

[78] Wolak, F. A. (2011). "Do Residential Customers Respond to Hourly Prices? Evidence from a Dynamic Pricing Experiment." *The American Economic Review*, 101(3), 8387. Retrieved from http://www.ingentaconnect.com/content/aea/aer/2011/00000101/00000003/art00015.

[79] Woo, C. K., Horowitz, I. and Sulyma, I. M. (2013). "Relative kW Response to Residential Time-Varying Pricing in British Columbia." IEEE Transactions on Smart Grid, 4(4), 1852-1860.

[80] Woo, C. K., Li, R., Shiu, A., and Horowitz, I. (2013). "Residential winter kWh responsiveness under optional time-varying pricing in British Columbia." *Applied Energy*, 108, 288-297.