University of New South Wales
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Honours Thesis

Residential Electricity Usage:

How Do Households Respond to Dynamic Peak Pricing Events?

Author:
Nathan Walsh
Student ID: 3372856

Supervisor:
Dr. Tess Stafford

Bachelor of Commerce (Financial Economics and Finance) (Honours)
and
Bachelor of Economics (Econometrics)

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Declaration

I hereby declare that this submission is my own work and that, to the best of my knowledge, it contains no material which has been written by another person or persons, except where due acknowledgement has been made. This thesis has not been submitted for the award of any degree or diploma at the University of New South Wales, or at any other institute of higher education.

Nathan Walsh
7th June, 2016

Acknowledgements and Dedication

Firstly, I would like to thank my supervisor Dr Tess Stafford for her advice and guidance over the last year. Her writing tips, draft feedback and ability to solve almost any problem have contributed greatly to this thesis. Additionally the other academic staff have provided helpful advice and support along the way. A special mention to Professor Denzil Fiebig who provided insightful feedback in the later stages.

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Abstract

Recent dynamic peak price trials have been effective in reducing electricity usage by between 10% and 50% during dynamic peak price hours (Farugui and Sergici, 2010). This thesis examines the extent of reductions in electricity usage for a dynamic peak price (DPP) and dynamic peak rebate (DPR) trial in N.S.W., Australia.

I find that households on a DPP trial reduce electricity usage by 29% and up to 34% if combined with feedback technology. Households on a DPR trial reduce usage by 11% but only 8% when combined with feedback technology.

The models are then extended to analyse if households' load shift from the more expensive peak event times to the relatively cheaper adjacent hours. I find that there is some evidence of load shifting for a number of treatment groups. Finally, I consider models for habit formation to determine whether experiencing multiple peak events will change households' behaviour throughout the trial. I conclude that if there is a break in peak events then households increase their electricity usage, but this effect reverses after repetition.

Chapter 1

Introduction

Dynamic peak pricing has been discussed as an alternative to standard flat rate and time of use pricing for a number of years. It provides a method by which electricity suppliers can offset the higher cost of electricity in the peak afternoon times on extremely hot or cold days. This is achieved by charging more for electricity at these times, reducing peak load.

Recent dynamic peak price trials have been effective in reducing usage by between 10% and 50% during dynamic peak events (Farugui and Sergici, 2010). This thesis contributes to the existing literature by analysing how households respond during dynamic peak price events when on a dynamic peak price (DPP) tariff or a dynamic peak rebate (DPR) in N.S.W, Australia. I then extend these models to consider whether households load shift. Load shifting occurs when households shift usage from the more expensive peak event times to the relatively cheaper periods prior to (and post) a peak event. Finally I consider whether households form habits as a result of experiencing peak events.

Only Wolak (2006) and Jessoe and Rapson (2014) have analysed load shifting and habit formation. Despite the lack of research these areas are important in understanding households' behaviour and the implications for the electricity suppliers. I provide a deeper analysis than has existed to date on the extent of load shifting and habit formation when households experience dynamic peak price events. Additionally I allow for household's habits to be more complex than that which has been considered in the past.

1.1 Motivation and Significance

Electricity demand varies greatly over the course of the year, month and day. As a result, the supply of electricity must also vary since storing electricity is difficult. When varying the supply of electricity to meet demand, suppliers encounter a wide range of marginal costs. The marginal cost of electricity varies over time for several reasons. Joskow and Wolfram (2012) outline several of these: 1. The demand for electricity varies considerably both throughout a day and across days. 2. It is uneconomical to store electricity in most situations. 3. The optimal mix of generating capacity to balance supply and demand at all hours given 1. and 2. includes a combination of base load capacity with high construction costs and low marginal operating costs, intermediate capacity with lower construction costs but higher marginal operating costs, and peaking capacity with the lowest construction costs and the highest marginal operating costs. At times when demand is low, base load capacity is sufficient. As demand rises, generating capacity with higher marginal cost is used to equate demand with supply. Typically marginal costs are lowest at night and higher in the afternoon periods. They become very high on extremely hot or cold days, depending on the price of substitute fuels and the generation methods available in a region.

Given the nature of the electricity market a standard flat tariff does nothing to equate the supplier's marginal cost with their marginal revenue. A policy to address this imbalance could reduce peak demand, raise peak marginal revenue, or achieve some combination of the two. This thesis focuses on the effects of policies that aim to reduce residential peak demand. In practice this is achieved through peak-load pricing which encompasses a range of pricing mechanisms and was first suggested more than 50 years ago by Kahn (1970) and Boiteux (1960).

Historically one of the methods that has been used to address this issue is "Time of Use" (ToU) pricing. ToU tariffs typically have high peak prices on weekday afternoons and lower off-peak prices throughout the rest of the week. Several experiments have been conducted by Atkinson (1979), Caves and Christensen (1980), Caves and Christensen (1984) and Herriges, Caves, and Christensen (1984) that suggest ToU pricing reduces demand in the high cost periods and increases usage in the off-peak periods. Whilst this will help address peak demand problems somewhat, on the extreme days when demand is at its highest, ToU pricing provides no additional incentive to reduce electricity usage. This is because ToU pricing only reflects long-term average expectations of daily peak marginal costs (Crew, Fernando, and Kleindorfer, 1995).

Until recently price based responses, such as dynamic peak pricing and real time pricing (RTP), had not been possible due to the limitations of the metering infrastructure. Older meters were unable to have two way communication and thus changes in price could not be immediately enacted. ToU pricing, with two or three different prices at a set time of the day, was the most flexible pricing mechanism that could be implemented. Now, new smart meters send real time consumption data to the utility provider and can receive notification of price changes in real time. Furthermore, developments in smart meter technology have seen the costs decline and functionality increase (Joskow and Wolfram, 2012). Communications, data storage, processing and acquisition have all improved drastically.

One such method that can now be implemented is real time pricing (RTP). These rates most closely relate time-dependent marginal wholesale costs with price. Allcott (2011) found that RTP does reduce peak demand as desired, however Kiesling (2008) found that RTP has a smaller effect than DPP in an experiment in Washington, with reductions of 15-17% for RTP and 20% for the DPP group. In general though, policy makers view RTP as too complex for small electricity users and are reluctant to allow residential customers to face the volatile wholesale market.

More recently dynamic peak pricing has been suggested and examined as a form of peak-load pricing. Dynamic peak pricing (also known as critical peak pricing) commits to several consecutive hours of high prices on a limited number of extreme weather days throughout a year. These extreme days are typically days that are predicted to be very hot or very cold and customers are notified in advance of the event times (often 30 minutes to 24 hours in advance).

Given the issues with ToU pricing and RTP, dynamic peak pricing is a desirable alternative. Dynamic peak pricing has the potential to mitigate the adverse impacts of high and volatile wholesale prices in several ways. Herter, McAuliffe, and Rosenfeld (2007) provide a summary of these benefits: 1. Dynamic peak pricing can be used to encourage decreased electricity usage during periods of low supply or high congestion. 2. Dynamic peak pricing can assist in lowering wholesale market prices by decreasing the need for electricity production from high cost peaking generators. 3. Dynamic peak pricing counteracts electricity wholesaler's ability to raise prices in the spot market. 4. It can be used to reduce the need for more peaking generators to be built. Evidently dynamic peak pricing has many benefits and is worthwhile considering as an alternative form of electricity pricing.

Chapter 2

Background Literature

In this chapter I outline the history of dynamic peak pricing, its implementation and performance in several studies throughout the world. I present some key findings which serve as a comparison to my findings in Chapter 5.

2.1 Recent Trials of Dynamic Peak Pricing

In 2003-2004 a dynamic peak price trial known as the Statewide Pricing Pilot (SPP) was conducted in California and analysed by Herter et al. (2007), Herter (2007) and Herter and Wayland (2010). Herter et al. (2007) found that households reduced their usage by 13% of baseline load, during temperature driven, five hour peak events.[1] This effect increases to 41% when combined with technology. Herter (2007) showed high-use customers respond significantly more than low-use customers in terms of kWh[2] reductions, but low-use customers save more in percentage reduction of annual electricity bills. Thus there are equity issues when deciding who should be placed on a dynamic peak price tariff. Herter and Wayland (2010) found that raising the price during dynamic peak events from \$0.50/kWh to \$0.68/kWh did not change households' responsiveness. Additionally they found that customers responses are dependent on dwelling characteristics and climate.

Another study carried out in California was the Advanced Demand Response System pilot in 2004-2005. This study was carried out on a subset of customers from the SPP and is discussed in (Rocky Mountain Institute, 2006). Participants in this program were still on a dynamic peak price tariff but also had an advanced home climate control system installed. This system enabled them to web-program their preferences for the control of home appliances. The dynamic peak price was three times the ToU price and the reductions in 2004 were as high as 51% and in 2005 were 43%. Since participants of the Advanced Demand Response System had load reductions

[1] Baseline load refers to load that would have otherwise occurred if there was not a peak event.

[2] kWh stands for kilowatt hours and refer to the amount of energy a device uses. For example an electric heater rated at 1000 watts (1 kilowatt), operating for one hour uses one kWh.

consistently larger than those without the technology (in the SPP program) it was concluded that technology was the main driver of these results.

A study was conducted in Missouri in 2004-2005 on dynamic peak pricing[3] and analysed by RLW Analytics (2004). Two treatment groups are of interest: Group 1 had ToU pricing with a DPP component, and Group 2 had ToU with a DPP component and technology (smart thermostat). These groups reduced their usage during dynamic peak periods by 12% and 35% in the Summer of 2004; the reductions during dynamic peak periods were 13% and 24% in the Summer of 2005. The difference in reductions during peak events in the following year is worth noting. Few trials have been able to consider households' responsiveness over an extended period of time. In this thesis I explore households behaviour over a similar period of time but focus more on the periods in-between peak events.

During the summer of 2005, the City of Anaheim Public Utilities ran a dynamic peak rebate experiment. Wolak (2006) examines the behaviour of households receiving a rebate of \$0.35/kWh if they reduced their usage below a baseline level and nothing if they did not lower usage. He found that households used 12% less electricity during peak events. Additionally there was no evidence of load shifting to days adjacent to a dynamic peak rebate event during peak or off-peak periods. There are a few problems with this experiment though: Firstly, the rebate calculation provided a strong incentive for households to increase their consumption during peak-periods on non-peak price days days. Secondly, the dynamic peak rebate mechanism guarantees that a customer's monthly bill does not exceed what the customer would pay under the standard increasing block tariff.

Wolak (2011) analysed data from the PowerCentsDC program which investigated the impact of a variety of price tariffs starting in July 2008. The paper considered three treatment group: RTP, DPP and a dynamic peak rebate (DPR) group (who receive a rebate for reducing usage during the peak event). The dynamic peak rebate and dynamic peak price groups are almost identical in regards to the prices faced and thus were pooled together to find a single estimate. Dynamic peak price and dynamic peak rebate events are found to result in households reducing usage by 9% on average across the year.

Faruqui and Sergici (2011) analysed data from a trial conducted in Baltimore. The study followed the same households over two consecutive summers in 2008 and 2009. It found that households participating in dynamic peak pricing in the summer of

[3]Throughout the paper RLW Analytics refers to these events as a Critical Peak Price events, but they are essentially the same as a Dynamic Peak Price (DPP) event. For the rest of this chapter I will refer to all peak events as DPP events.

2008 with no feedback technology reduced their usage by 20%. Those with a dynamic peak price tariff and feedback technology reduced their usage by 32.5% on average in the Summer of 2008. Additionally a treatment group that received a rebate was analysed. The households that received a rebate but had no technology reduced usage by 18% with a low rebate and 21% if they had a higher rebate. If they were given feedback technology this increased to 23% and 26.8%. Finally if they received technology and had an air conditioning switch, so that the supplier could remotely turn off their air conditioning, the effect increased to 28.5% and 31%. The following year the same households seemed to be just as responsive in the similar treatment groups.

Ida, Ito, and Tanaka (2013) conducted an experiment in which households with in home displays experienced several different peak prices. Households were notified a day in advance that the price would be one of five values. The reduction in usage during peak events was found to vary with price in a statistically significant manner. When the price was \$0.15/kWh electricity usage dropped by 5%. When the price was increased to \$0.45/kWh the reduction in usage was 14%. When the price increased to \$1.50/kWh, the reduction was 18%. Thus they conclude that increasing prices results in larger reductions but these reductions decrease as price increases.

Jessoe and Rapson (2014) conducted a study over two months in Connecticut. They found that households without in home displays (IHDs) did not respond to dynamic peak price events whereas households with IHDs reduced usage by 14%. Additionally they found that households with IHDs that were notified of a dynamic peak event a day in advance will load shift. In particular they will decrease their usage by 10% on average both 2 hours prior and 2 hours post event. Evidence of habit formation was also picked up over the two months of the trial. They estimate the change in electricity usage by hour of day and find that for the peak hours (noon-8pm) households decrease their hourly electricity usage by between 0.25% and 0.4% each day, depending on the hour.

Table 2.1 summarises the key results from these papers.

Table 2.1: Summary of Relevant Literature

Paper	Price Increase for Peak Event (%)	Change in Usage - Price only Group	Change in Usage - Price+Technology Group	Technology	Location
Heter (2007)	360	13	41	AC Switch	California
Rocky Mountain Institute (2006)	300		51	AC Switch	California
RLW Analytics (2004)	Undisclosed	12	35	AC Switch	Missouri
Wolak (2006)	Rebate of \$0.35/kWh	12			Los Angeles
Wolak (2011)	550	9			Columbia
Faruqui and Sergici (2011)	800	20	32.5	IHD	Baltimore
Ida, Ito and Tanaka (2013)	200 to 900	9 to 13			Kitakyushu
Jessoe and Rapson (2014)	250	7	17	IHD	Connecticut

Notes: The technology used in these trails were all slightly different. The main function of the air conditioner switch (AC Switch) was to allow the supplier to turn down or off the air conditioner during peak price events.

The estimation method I use in this study is similar to Wolak (2011) however I do not combine the dynamic peak price and dynamic peak rebate groups. I also extend his model to consider other dynamics that may occur throughout the trial. In the papers mentioned above, generally larger price increases during dynamic peak events results in larger reductions in usage. Furthermore households appear to respond similarly across time, with responses to dynamic peak events a year later being very similar. These two observations are important when considering my data since households received a large price increase and are monitored for over a year.

These papers also find decreases in usage during dynamic peak price events vary widely depending on a number of factors. In particular the magnitude of the price increase during peak events and the presence of feedback technology alter household's responsiveness. When a very small price increase occurs such as in Ida et al. (2013), an increase of only a few cents, the resulting reduction is only 5%; when the increase is more moderate it can be up to 41% as in Herter (2007).

There is also conflicting evidence of load shifting. Wolak (2006) finds that households do not load shift to adjacent days but Jessoe and Rapson (2014) find that households do load shift in the 2 hours before and after an event if given feedback technology. Finally very few papers analyse the existence of habit formation, due predominately to the short time period in which these trials take place. Thus in this study I shall further examine these areas and expand on the existing literature.

Chapter 3

Experimental Design

The Smart Grid, Smart City Program ("Program") was part of the Australian Government's Energy Efficiency Initiative. It was intended to deliver Australia's first demonstration and/or commercial-scale rollout of smart grid technologies. The Program was one of the largest and most ambitious commercial-scale trial deployments of smart grid infrastructure in the world and was conducted from 2012-2014.

The Program was largely focussed on the greater Newcastle and Sydney CBD areas with some additional areas selected to test specific smart grid applications unrelated to this paper. The greater Newcastle area was selected as one of the focal points for the Program due to its mix of regional and suburban characteristics that result in geography, climate, socioeconomic and demographic factors that are representative of Australia. Newcastle's close relationship to the Australian average for customer demographics is widely accepted and has resulted in the city being used as a test market for products and services prior to their rollout across Australia in the past.

Within the different local government areas there were over two million people which equates to over one million households. From this population 7,612 households participated in the Program and were assigned one of three price tariffs. Some of these households also received feedback technology.

3.1 Pricing Design

Prior to the Program, participants were on either a flat tariff ("All Time") or a time of use ("ToU") tariff. With the original price structures customers on an All Time plan paid the same rate all day, every day. For customers on a ToU plan, the rate varied according to the time of day as per the first panel in Figure 3.1.

Once participants began the Program they were assigned one of three pricing designs. One of the tariffs involved no change to the household's original price structure. This pricing design was applied to the control group so that the effects of the other two tariffs could be compared to some baseline.

Another price design was the Dynamic Peak Price (DPP) tariff. This involved changing the cost per kWh of electricity as per Figure 3.1. Once the Program began the treatment groups with a DPP tariff had their price changed to 24.53 cents per kWh between 7am and 10pm and 13.09 cents outside this time. During peak events the price spiked to 330.00 cents, an increase of more than 1200%. The new pricing design was developed so that a customer's annual bill would be cost neutral if they made no behavioural change during peak events. Additionally, there were further opportunities to save if participants reduced their usage during the peak price events. This meant that the peak rate (defined as the rate between 2pm to 8pm) was reduced in order to create cost neutrality. More details on the treatment group characteristics are discussed in the Sample Design section.

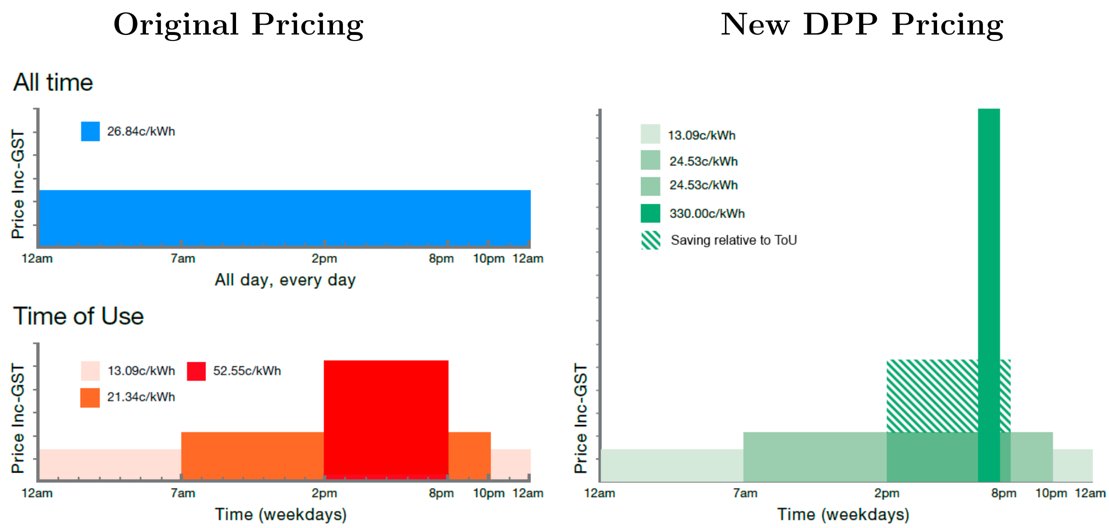

Figure 3.1: Pricing Design, adapted from AEFI (2014)

The second tariff applied to some treatment groups was the Dynamic Peak Rebate (DPR) tariff. Participating customers received a rebate ranging from \$0 to over \$100, depending on how much their electricity consumption was reduced compared to their baseline use on days with similar temperature, at the time of the peak price event. The average rebate was estimated to be \$20 per event for both households with and without feedback technology. The exact rebate calculation was not revealed to the customers and there is evidence that the correlation between kWh savings and rebates was not strong (Frontier Economics, 2014). The implications of this will be discussed in Chapter 5.

3.2 Technology

In addition to the three tariffs, three feedback technologies were trialled. These included an in-home display (IHD), an online portal and smart plugs. Participants were randomly assigned into a group with no feedback technology, one feedback technology or two feedback technologies.

The in home display (IHD) is a small portable device which provides customers with near real time pricing and electricity usage information. Text messages were sent to households to inform them of price changes or peak events via the IHD [1]. Figure 3.2 shows an IHD and provides a brief explanation of their functionality.

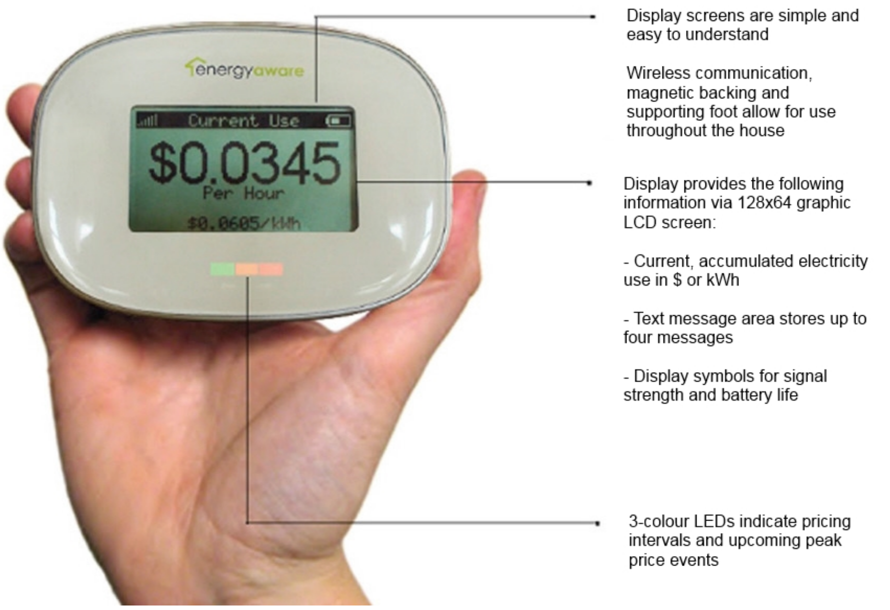

Figure 3.2: In-Home Display, sourced from AEFI (2014)

Access to an online portal was provided to certain treatment groups. This enabled them to view their current electricity usage in real time on a computer, tablet or smart phone (available on both Apple and Android). Electricity usage could be displayed in increments of weeks, months or a year. Greenhouse gas emissions could be estimated based on a household's electricity usage. The portal had the ability to compare a customer's usage with that of other households. Monthly competition draws were available via the portal. Activities that could earn points for entrants to then be in the running for a prize included: daily logins, competition enrolment and weekly quizzes. Figure 3.3 displays an example of the interface customers in this treatment group experienced.

[1] This is in addition to text messages that were sent to households 24 and 2 hours prior to a dynamic peak event

Smart plugs were provided to two of the treatment groups (see Figure 3.4). This enabled them to analyse their electricity consumption at the device level. Up to ten individual devices that plugged into a general power outlet could be sub-metered and controlled by a smart plug. The smart plug enabled devices to be switched on and off in response to a command received by the smart meter. This command would be sent by the customer from either the online portal or a mobile device. The smart plug calculated the electricity usage of the relevant appliance and the instantaneous power demand. Every 30 minutes the smart meter would wirelessly collect total accumulated consumption, this was then sent to the online portal to show the appliance breakdown for all sub-metered appliances.

Figure 3.3: Online Portal, sourced from AEFI (2014)

Figure 3.4: Jetlun Smart Plug, sourced from Jetlun

3.3 Sample Design

The pricing schemes and technologies were interacted to form 11 groups. Table 3.1 provides an overview of the size of the treatment and control groups. The control group contains 2,092 households, more than the vast majority of experiments conducted to date.

Table 3.1: Size of Treatment and Control Groups

Technology	**Price**			
	DPP	DPR	None	**Total**
IHD only	1,048	661	666	2,375
Portal only	338	0	1,325	1,663
IHD and Portal only	0	0	178	178
Smart Plug and Portal only	142	0	65	207
None	415	682	2,092	3,189
Total	1,943	1,343	4,326	7,612

3.4 Customer Selection and Communication

To ensure a representative sample was selected, a sampling trial and trial design project was undertaken. Futura Consulting, in collaboration with Taylor Fry

Consulting, were engaged by Ausgrid to assist in the development of the sample design. The resulting report is known as the Futura Report (2011) and its recommendations were as follows.

The report found that several variables were important in influencing electricity usage, electricity efficiency and electricity conservation behaviour. These variables were recognised as a complex mix of physical factors such as appliance ownership and climate, socio-demographic factors such as income, age and dwelling size and psychographic factors that include customer attitudes, beliefs and values. A wide ranging literature review was undertaken to determine the appropriate socio-demographic variables to consider when selecting a sample. Thus a stratified sample was created based on the final sampling variables (referred to as covariates) suggested by Futura Consulting. These were: electricity usage, climate, income, dwelling type and gas consumption. Details of these variables, the rationale for their inclusion and the rationale for those variables excluded are contained in the Futura Report Futura Consulting (2011).

Households were divided into three different categories of income, two dwelling types (unit and not unit), two climate zones (warm temperate and mild temperate), three levels of electricity usage and three levels of gas consumption as per Table 3.2. The product of all these different categories resulted in 108 different customer cells (3*2*2*3*3). The number of participants required to trial each of the combinations of feedback technology and price tariff was calculated based on the following constraints, assumptions and estimates:

- Total available population (i.e. residential dwellings matching within the Program defined areas that are eligible to partake in the trial)
- Population of each cell within the Program defined area (i.e. every available household within the Program area was allocated to a cell based on the known or inferred values of each covariate)
- Limited number of meters available to be installed
- Limited number of physical feedback devices available to be installed
- Expected take up rates of each product
- Expected opt out rates for each product
- Control group minimum size requirements (more than 600 households)

Further constraints were placed upon the selection of customers as the Program progressed and more constraints were determined (for example, the signal from the smart meter to the receiver may have been insufficient). Due to a mixture of experiment design and constraints encountered throughout the Program, there is significant variation in the size of the treatment groups. Despite the variations in size the results are unlikely to be impacted since the smallest group still has 65 households and the others have up to 2000.

The final list of all constraints that were placed on the customer selection process for the Network Trial and associated control group are included in Appendix A - Additional Research Design Information.

Table 3.2: Covariate Breakdown

	Income (p.a)	Electricity Usage (kWh per year)	Gas Usage (MJ/Day)
Low	$\leq$ \$41,600	1,000-4,500	<38.165
Med	\$41,600-62,400	>5,400-9,000	38.165 to <56.474
High	$\geq$ \$62,400	>9000	>56.474

Based on electricity usage, climate, income, dwelling type and gas consumption, the sample and trial design defined the number of households that were required to be made an offer for each treatment group and the control group, a total of 11 groups, for each cell (i.e. a 11 x 108 matrix containing the number of offers required). This process is displayed in Figure 3.5 and Figure 3.6.

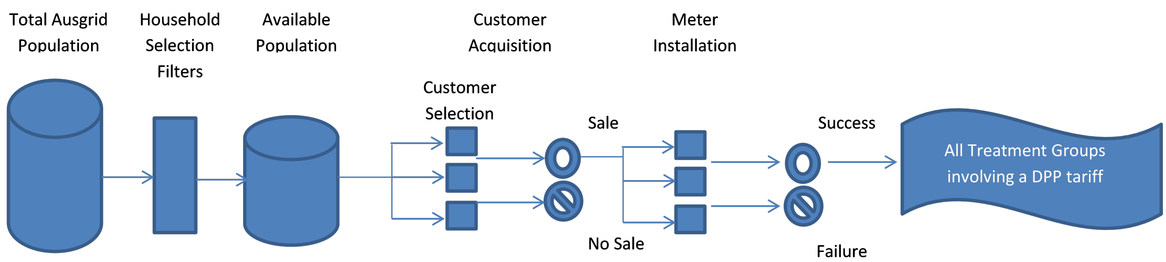

Figure 3.5: DPP Treatment Group Customer Acquisition Process, adapted from Ausgrid (2014)

There was a difference in household acquisition procedure due to the tariffs applied to the different treatment groups. Although the DPP tariff was designed to be cost neutral, the treatment groups which had a DPP tariff could have received higher bills. Thus these households had to agree to participate in the Program prior to the smart meter being installed. The other treatment groups had either no change in the price structure or were on a DPR tariff, whereby they were receiving extra money

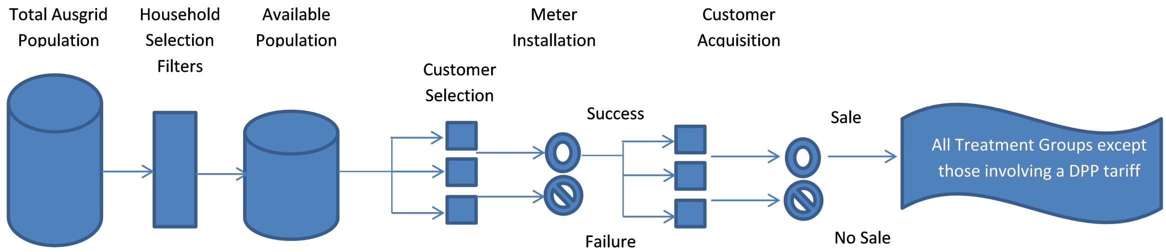

Figure 3.6: Control and DPR Treatment Group Customer Acquisition Process, adapted from Ausgrid (2014)

for using less electricity. Hence these treatment groups had smart meters installed and then were approached to participate in the Program once their smart meters were confirmed to be working. Whether people were approached pre-installation or post-installation is of minimal significance since households would not change their behaviour if the only thing that changed was the meter sitting outside their house. What is important is that households were randomly selected to the control or one of the treatment groups (subject to some non-restrictive constraints mentioned in Additional Research Design Information) and that people were randomly assigned to a treatment group, conditional on them being willing to participate in the Program.

The customers that already had a properly functioning smart meter installed were made an offer to participate in the Program as part of the control group or a DPR tariff group. There were three methods through which customers were asked to participate.

1. Door to door: Ausgrid expected to achieve the majority of households acceptances using door to door sales, since this method typically provides the highest conversion rates.

2. Telephone: Telemarketing was used to contact customers who could not be contacted via door to door, as well as to call customers in low-density areas in which it was not cost effective to travel door to door.

3. Direct mail: A mail offer was sent to customers who could not be contacted via door to door or telesales. This ensured that all customers that had a properly functioning smart meter had an opportunity to participate in the Program.

Before being assigned to the control group or a DPR treatment group, participants were asked basic questions to determine their characteristics and ensure they were eligible to participate. This was entered into an iPad or desktop computer and then software would allocate the customer to one of the treatment groups. This software automatically assigned customers to a treatment group based on their profile and which targets needed to be filled (of the 108 customer types).

For the customers who were to be invited to participate in the DPP Program a similar method was used to approach customers. Both door to door and telesales were used and sales representatives were provided with software for scripting, customer qualification questions and product information which ultimately determined which combinations of technology were offered to customers. This ensured that the selection of customers and assignment to treatment groups were based on the sampling and trial design process discussed earlier.

Participants were in any of the DPP and DPR treatment groups were notified both 2 and 24 hours in advance as to when a dynamic peak price event would occur. These notifications were sent as a text message to phones and to households' IHDs (if they had one).

Chapter 4

Data

The primary outcome analysed is household electricity usage via high frequency meter data. Every household had a smart meter installed that captured electricity usage in 30 minute intervals. Some households were signed up to the Program as early as October 2011 and data collection began in February 2012. Households were progressively phased into the Program as they were signed up. By Janurary 2013 75% of households were participating in the Program and this had risen to 90% by April 2013. The data collection finished in early March 2014 when the Program finished.

The timing and duration of peak events along with information on the tariff and feedback technology a household was assigned, is used in the models. Finally a survey conducted during the Program included many household variables such as income group, electricity usage group, gas usage group, dwelling type, local government area, number of children, air conditioning type and whether occupants were home during the day.

Many households did not respond to all the survey questions, for example only 17% of households reported their income group and dwelling type. To resolve this problem individual household's Local Government Areas (LGAs) were used to estimate their income level. Additionally the dwelling type was inferred based on number of electricity meters at an address. If there were more than 5 then it was assumed the property contained units. The electricity usage of the household could be calculated since Ausgrid was the network service provider and the gas usage could be calculated at the household level using data supplied by a gas company. Thus income and dwelling type variables suffer from some level of inaccuracy but this is hard to quantify without further information. Other variables, such as number of fridges, number of children, type of air conditioning and whether occupants are home during the day, were also unreported by a large number of households.

4.1 Mean Differences

To determine if there are any large differences between treatment and control groups, I present a table of summary statistics by group. Tables 4.1 and 4.2 contain the difference in mean between the control and each of the treatment groups for the household variables of interest. The mean differences table for the treatment groups that do not experience peak events is included in Appendix B

Table 4.1: Mean Differences - Control, DPP, DPP+IHD and DPP+Portal

	Control	DPP only		DPP+IHD		DPP+Portal	
	Mean	Mean	Difference	Mean	Difference	Mean	Difference
Income							
- Low {0,1}	0.405	0.270	−0.135∗∗∗	0.330	−0.075∗∗∗	0.287	−0.118∗∗∗
	[0.491]	[0.444]	[0.026]	[0.470]	[0.018]	[0.453]	[0.028]
- Med {0,1}	0.329	0.316	−0.013	0.357	0.028	0.376	0.047
	[0.470]	[0.465]	[0.025]	[0.479]	[0.018]	[0.485]	[0.028]
- Hi {0,1}	0.266	0.414	0.148∗∗∗	0.313	0.047∗∗	0.337	0.071∗∗
	[0.442]	[0.493]	[0.024]	[0.464]	[0.017]	[0.473]	[0.026]
Gas Usage							
- Low {0,1}	0.361	0.441	0.080∗∗	0.600	0.239∗∗∗	0.527	0.166∗∗∗
	[0.480]	[0.497]	[0.026]	[0.49]	[0.018]	[0.500]	[0.028]
- Med {0,1}	0.461	0.369	−0.093∗∗∗	0.292	−0.169∗∗∗	0.269	−0.192∗∗∗
	[0.499]	[0.483]	[0.027]	[0.455]	[0.018]	[0.444]	[0.029]
- Hi {0,1}	0.178	0.190	0.013	0.108	−0.070∗∗∗	0.204	0.026
	[0.382]	[0.393]	[0.021]	[0.310]	[0.014]	[0.404]	[0.023]
Electicity Usage							
- Low {0,1}	0.492	0.475	−0.017	0.448	−0.044∗	0.429	−0.063∗
	[0.500]	[0.500]	[0.027]	[0.497]	[0.019]	[0.496]	[0.029]
- Med {0,1}	0.275	0.299	0.023	0.300	0.024	0.337	0.062∗
	[0.447]	[0.458]	[0.024]	[0.458]	[0.017]	[0.473]	[0.026]
- Hi {0,1}	0.233	0.227	−0.006	0.253	0.020	0.234	0.001
	[0.423]	[0.419]	[0.023]	[0.435]	[0.016]	[0.424]	[0.025]
Dwelling Type							
- Unit {0,1}	0.300	0.137	−0.162∗∗∗	0.102	−0.198∗∗∗	0.086	−0.214∗∗∗
	[0.458]	[0.345]	[0.024]	[0.303]	[0.016]	[0.280]	[0.026]
- Not Unit {0,1}	0.700	0.863	0.162∗∗∗	0.898	0.198∗∗∗	0.914	0.214∗∗∗
	[0.458]	[0.345]	[0.024]	[0.303]	[0.016]	[0.280]	[0.026]
Number of HHs	2092	415		1048		338	

Notes: The means are reported by treatment group, with standard deviations in brackets below. "Difference" displays the difference in means between each treatment group and the control, with standard errors in brackets below.
***Significant at the 1% level
**Significant at the 5% level
*Significant at the 10% level

Table 4.2: Mean Differences - Control, DPP+Plug, DPR and DPR+IHD

	Control	DPP+Portal+Plug		DPR only		DPR+IHD	
	Mean	Mean	Difference	Mean	Difference	Mean	Difference
Income							
- Low {0,1}	0.405	0.239	−0.165***	0.337	−0.068**	0.366	−0.039
	[0.491]	[0.428]	[0.042]	[0.473]	[0.021]	[0.482]	[0.022]
- Med {0,1}	0.329	0.324	−0.005	0.320	−0.009	0.297	−0.032
	[0.470]	[0.470]	[0.041]	[0.467]	[0.021]	[0.457]	[0.021]
- Hi {0,1}	0.266	0.437	0.170***	0.343	0.077***	0.337	0.071***
	[0.442]	[0.498]	[0.039]	[0.475]	[0.02]	[0.473]	[0.020]
Gas Usage							
- Low {0,1}	0.361	0.423	0.062	0.346	−0.015	0.333	−0.028
	[0.480]	[0.496]	[0.042]	[0.476]	[0.021]	[0.472]	[0.021]
- Med {0,1}	0.461	0.359	−0.102*	0.356	−0.105***	0.360	−0.101***
	[0.499]	[0.481]	[0.043]	[0.479]	[0.022]	[0.48]	[0.022]
- Hi {0,1}	0.178	0.218	0.040	0.298	0.120***	0.307	0.129***
	[0.382]	[0.415]	[0.033]	[0.458]	[0.018]	[0.462]	[0.018]
Electicity Usage							
- Low {0,1}	0.492	0.479	−0.013	0.491	−0.001	0.486	−0.006
	[0.5]	[0.501]	[0.043]	[0.500]	[0.022]	[0.5]	[0.022]
- Med {0,1}	0.275	0.232	−0.043	0.318	0.043*	0.310	0.035
	[0.447]	[0.424]	[0.039]	[0.466]	[0.02]	[0.463]	[0.02]
- Hi {0,1}	0.233	0.289	0.056	0.191	−0.042*	0.204	−0.029
	[0.423]	[0.455]	[0.037]	[0.393]	[0.018]	[0.403]	[0.019]
Dwelling Type							
- Unit {0,1}	0.300	0.021	−0.279***	0.264	−0.036	0.257	−0.043*
	[0.458]	[0.144]	[0.039]	[0.441]	[0.020]	[0.437]	[0.020]
- Not Unit {0,1}	0.700	0.979	0.279***	0.736	0.036	0.743	0.043*
	[0.458]	[0.144]	[0.039]	[0.441]	[0.020]	[0.437]	[0.02]
Number of HHs	2092	142		682		661	

Notes: The means are reported by treatment group, with standard deviations in brackets below. "Difference" displays the difference in means between each treatment group and the control, with standard errors in brackets below.
***Significant at the 1% level
**Significant at the 5% level
*Significant at the 10% level

The mean differences between the control and each of the treatment groups show a statistically significant difference in means for a number of the variables (denoted by the stars). The income category tends to be statistically different between the control and each of the treatment groups for both low and high usage but not medium. Perhaps more importantly, the electricity usage for all categories does not differ between the control and each of the treatment groups at the 5% significance level. As mentioned earlier, some of these variables, such as income category and dwelling type, had to be assumed. Thus the mean differences for these variables may be somewhat inaccurate. Gas usage on the other hand was sourced from the supplier and can be regarded as accurate.

It appears that the DPP+IHD treatment group has more low gas users and fewer medium and high users. When interpreting the results for the DPP+IHD treatment group it is important to remember that they were likely to be higher users of electricity already, since they use low amounts of gas, and thus have more ability to decrease electricity usage compared to other groups. There are also less households that live in a unit in each of the DPP groups compared to the control group which means this group is likely to consume less electricity. The effect on electricity usage of living in a unit may balance to some extent with the low gas usage of these households. Thus the electricity usage appears to be fairly evenly distributed across the groups when it is in fact due to other reasons. Regardless of the differences between the control and treatment groups, the models I will use take into account the inherent differences between households, including the treatment groups they are assigned to.

4.2 Frequency of Events

DPP and DPR events were scheduled during 2013 and early 2014. Figures 4.1 and 4.2 show when the peak events occurred. It is also important to note that the number of customers participating in these events increases drastically after the first few events. This is due to households still being invited to participate in the Program and the length of time required to install smart meters and technology in households. After a couple of events had passed the number of households in the Program reached a relatively stable level. Whilst this is not ideal the households that joined the Program initially are relatively similar to those that joined later.

Table A.1 and A.2 in Appendix A show the timing and duration of the different events. Events range from two to fours hours and start and finish on the hour or half past the hour.

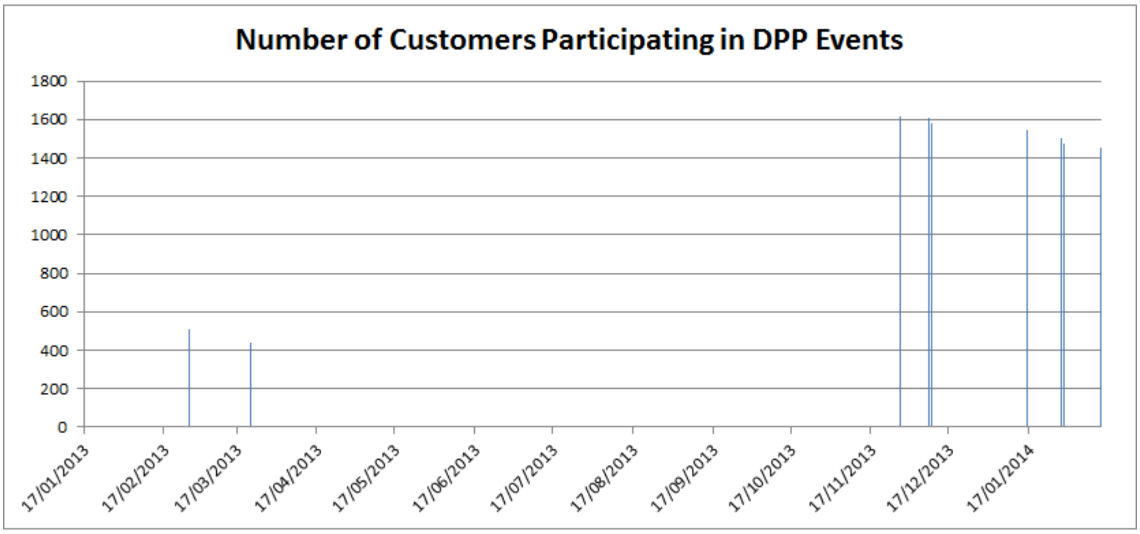

Figure 4.1: DPP Event Timing

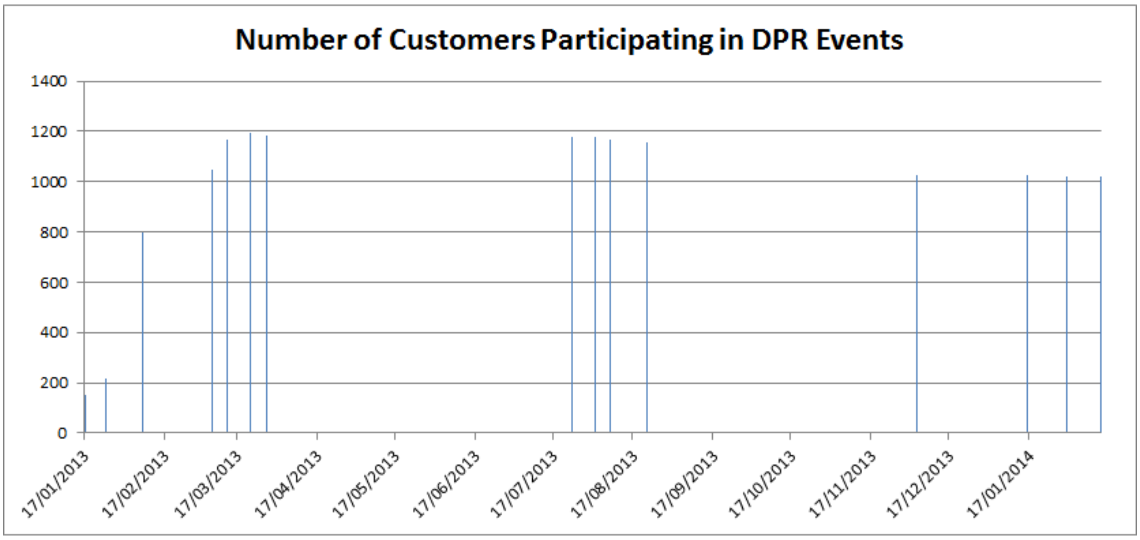

Figure 4.2: DPR Event Timing

4.3 Graphical Analysis

In order to gain an initial understanding of what is happening during peak events, I graph all the treatment groups responses during the peak events.

Figures 4.3 - 4.11 depict the average usage for each group with a DPP tariff, on DPP event days. In nearly all the events it appears that the DPP treatment groups respond (to varying degrees) to the peak price events. Generally the treatment groups reduce their usage to below that of the control group, during peak events. An exception is Figure 4.3, where the treatment groups reduce their usage, but not to a level lower than the control group. What is important is that their usage is declining *relative* to the treatment group. There is also some evidence of load shifting; we see spikes in electricity usage immediately before and after peak events. Furthermore the spikes surrounding the peak events appear symmetric such that the increase before a peak price event is of similar size to the increase after a peak price event, relative to the control group.

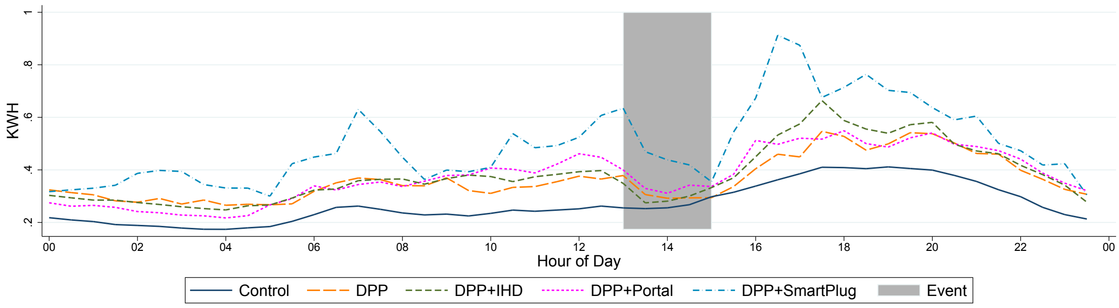

Figure 4.3: DPP 2013-02-26

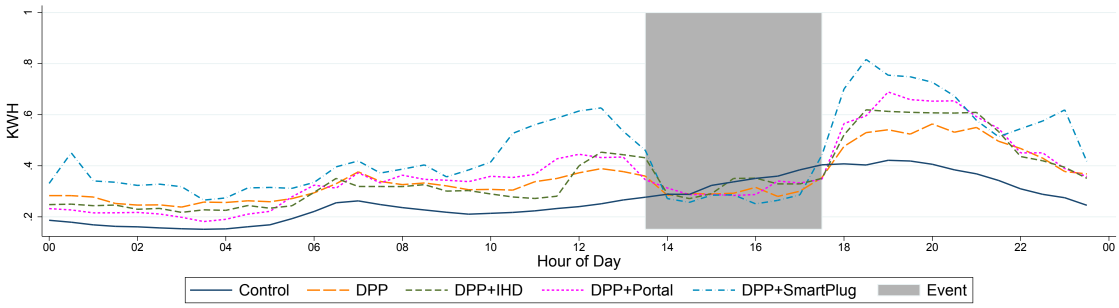

Figure 4.4: DPP 2013-03-22

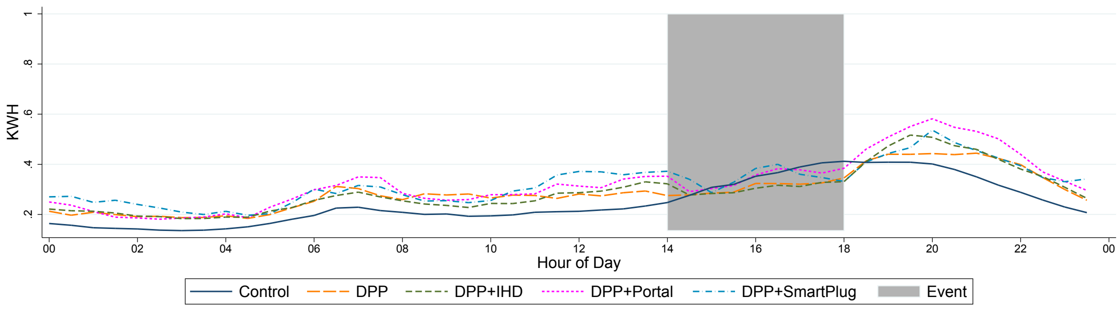

Figure 4.5: DPP 2013-11-28

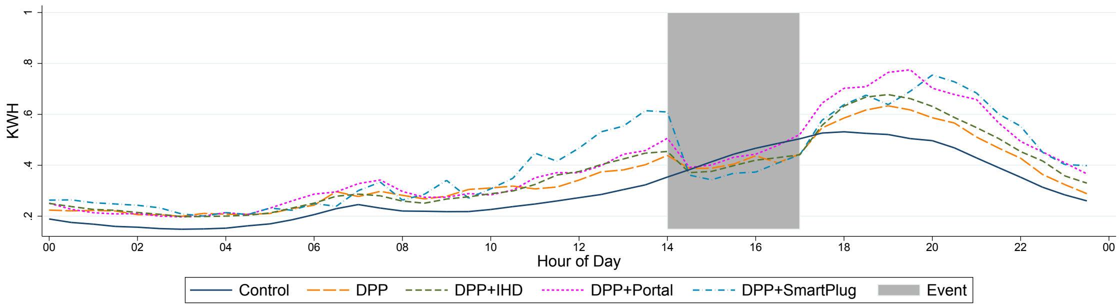

Figure 4.6: DPP 2013-12-09

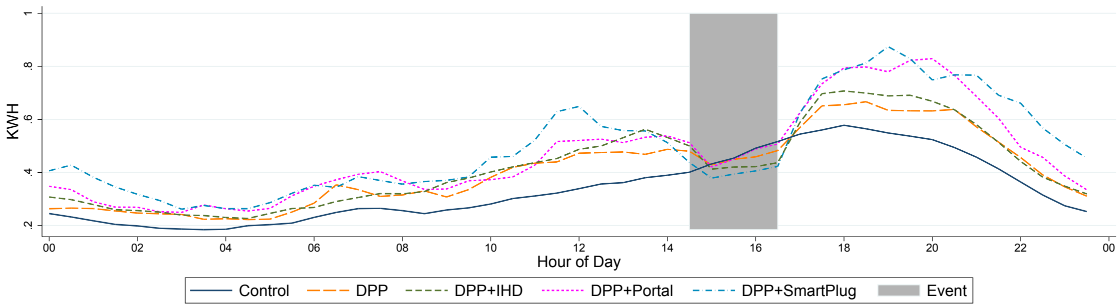

Figure 4.7: DPP 2013-12-10

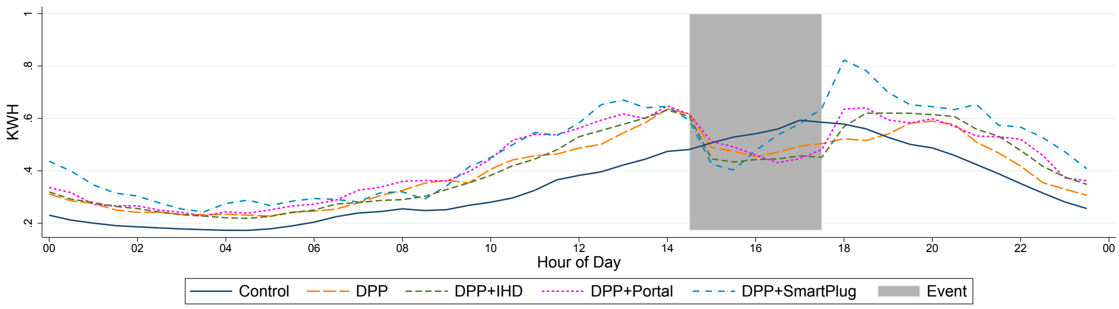

Figure 4.8: DPP 2014-01-16

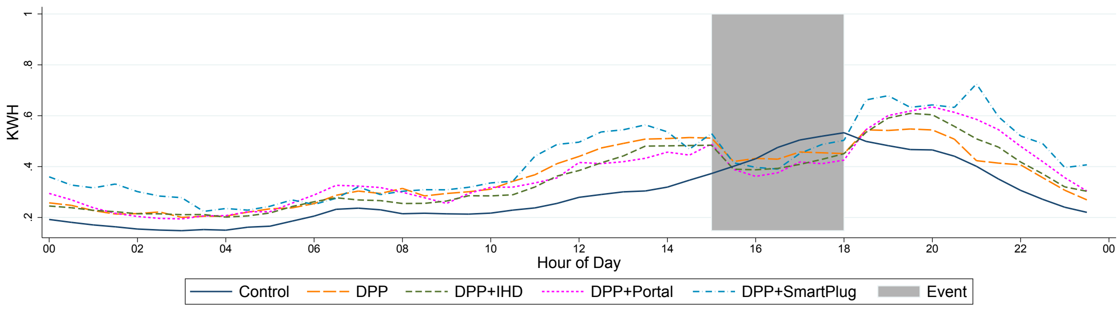

Figure 4.9: DPP 2014-01-29

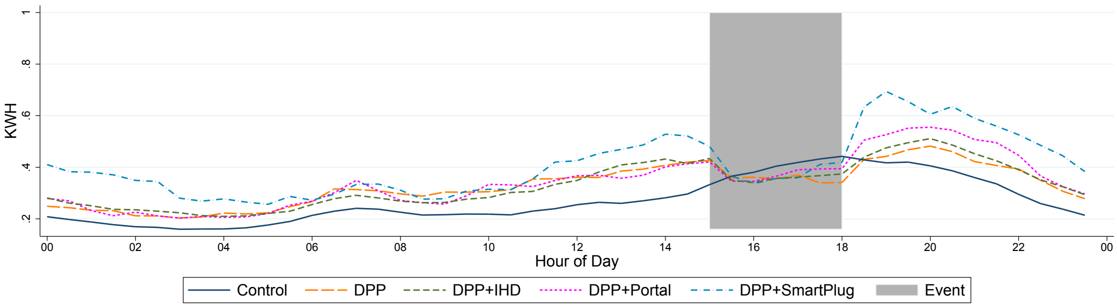

Figure 4.10: DPP 2014-01-30

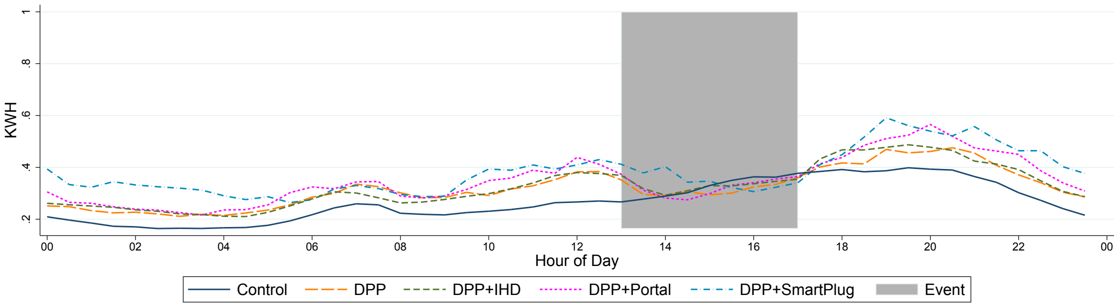

Figure 4.11: DPP 2014-02-13

Figures 4.12 - 4.26 show the DPR treatment groups responding to many of the peak events. The magnitude of the responses appear smaller than during the DPP events. Whilst it appears that the treatment groups are responding minimally to the peak events, the scale must be considered. As a percentage reduction relative to the control group, the responses appear to still be as large as 10% during some events.

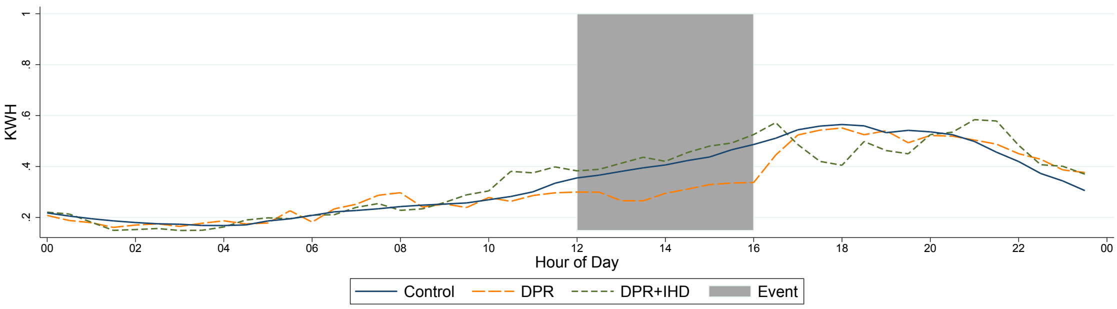

Figure 4.12: DPR 2013-01-17

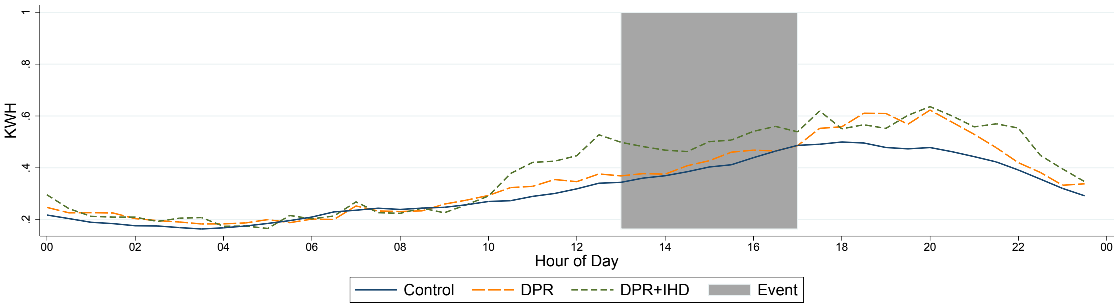

Figure 4.13: DPR 2013-01-25

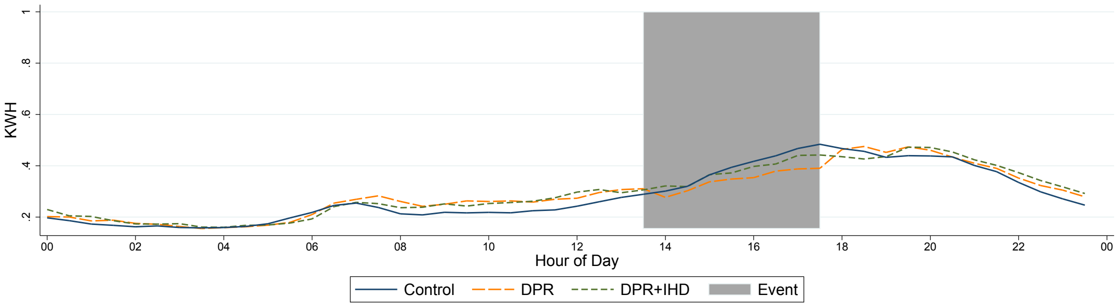

Figure 4.14: DPR 2013-02-08

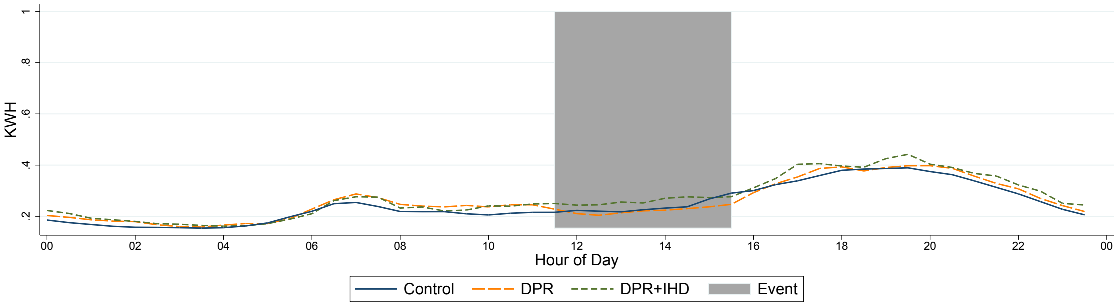

Figure 4.15: DPR 2013-03-07

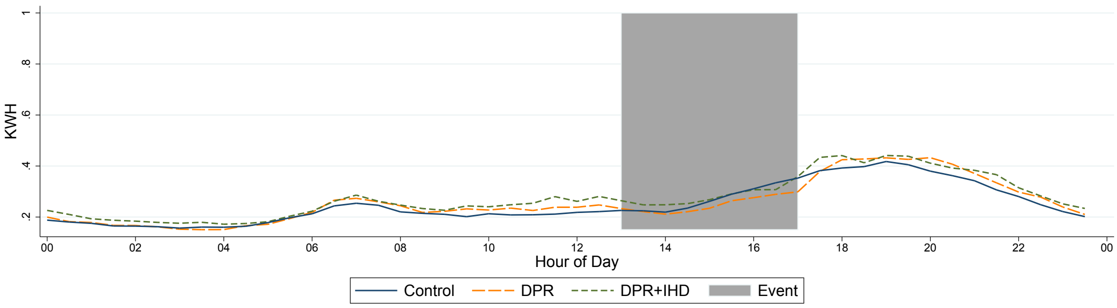

Figure 4.16: DPR 2013-03-13

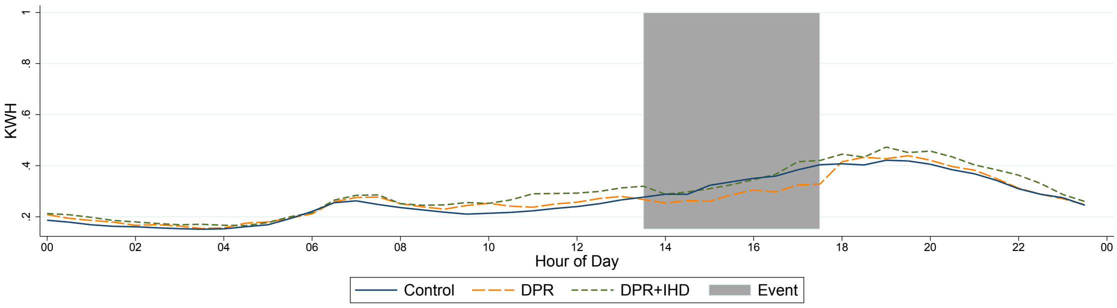

Figure 4.17: DPR 2013-03-22

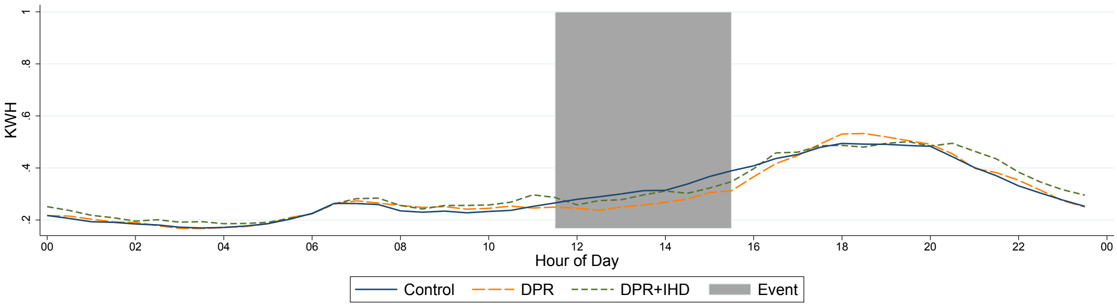

Figure 4.18: DPR 2013-03-28

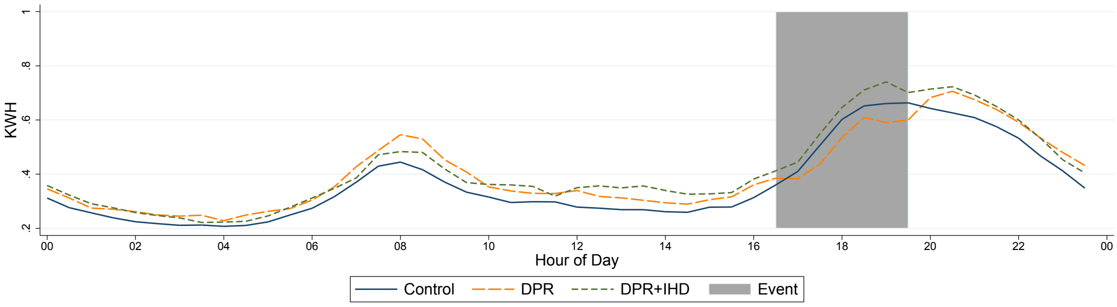

Figure 4.19: DPR 2013-07-24

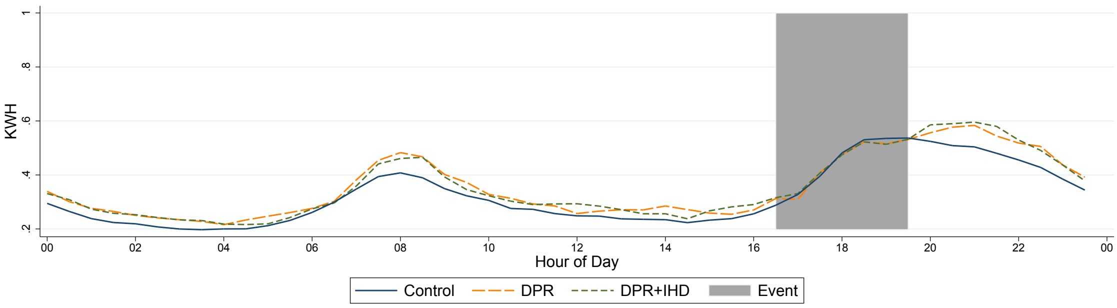

Figure 4.20: DPR 2013-08-02

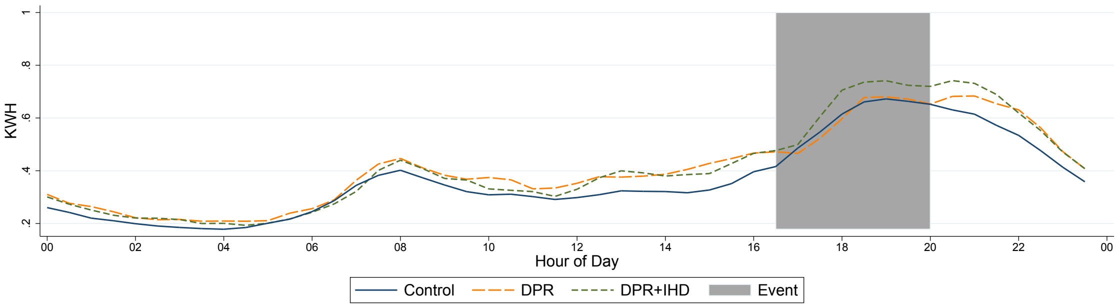

Figure 4.21: DPR 2013-08-08

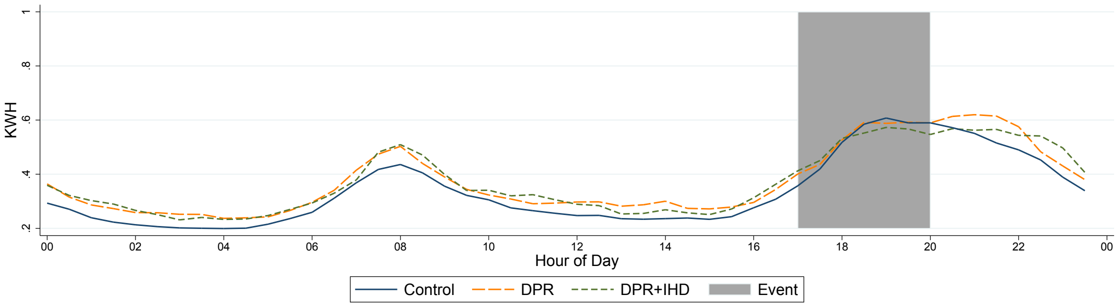

Figure 4.22: DPR 2013-08-22

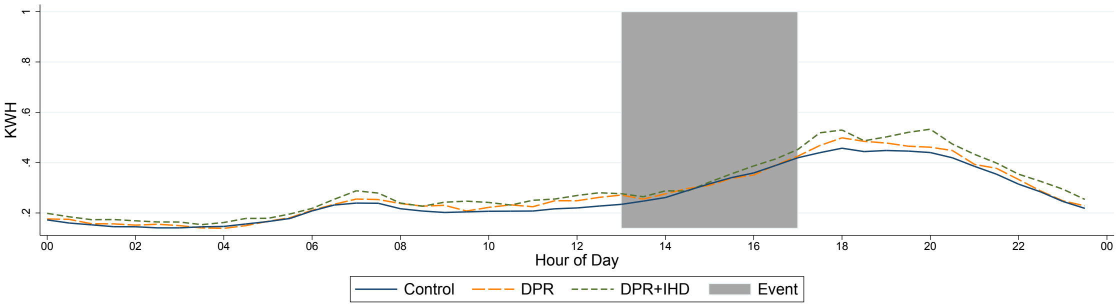

Figure 4.23: DPR 2013-12-04

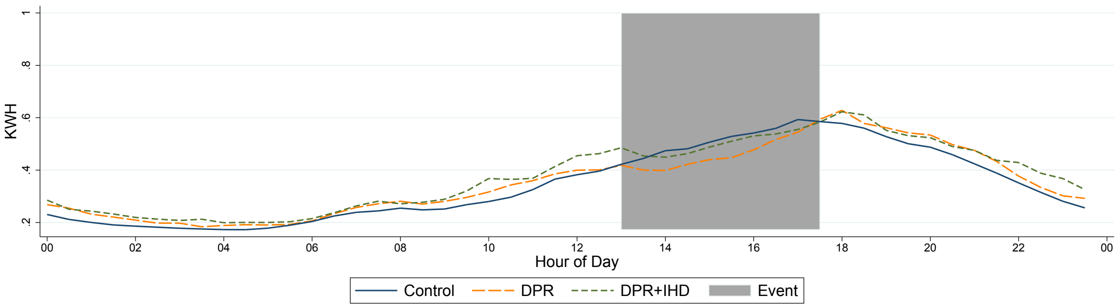

Figure 4.24: DPR 2014-01-16

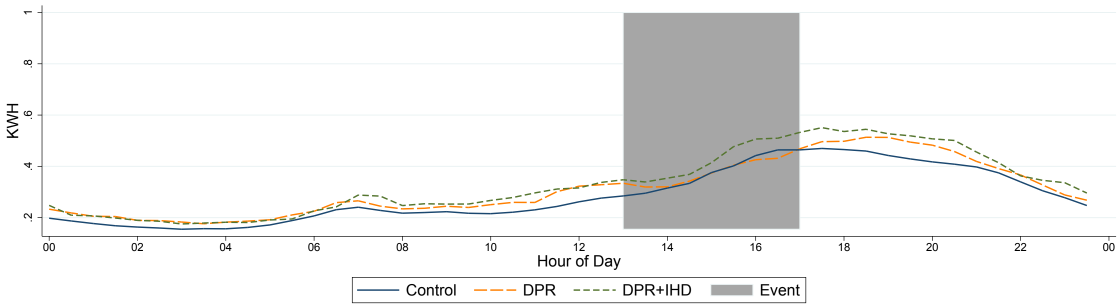

Figure 4.25: DPR 2014-01-31

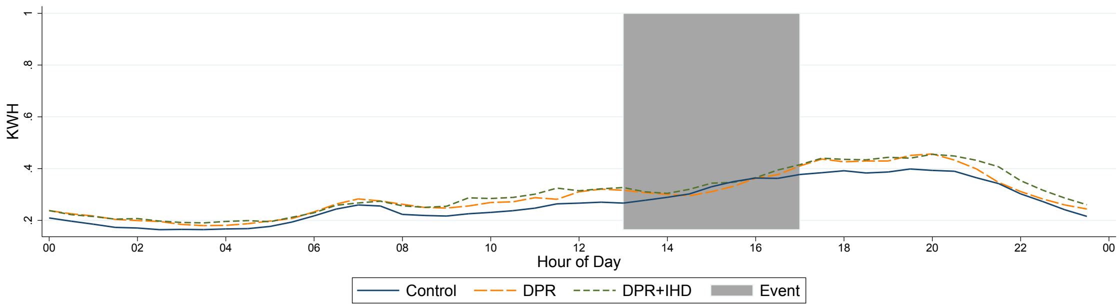

Figure 4.26: DPR 2014-02-13

Figures 4.27 to 4.30 are graphs of non event days for the different treatment groups. I randomly selected a number of days which occurred near a peak event as a comparison to see how the control and treatment groups average usage appears on non-event days. It appears that the DPP treatment groups consistently have higher consumption than the control group and the DPR groups are more similar to the control group. However as shown earlier the mean difference for electricity usage between control and treatment groups is not statistically significant or economically significant. Thus it would be easy to think that the difference between the DPP groups and the control on non-event days can be considered inconsequential. However the electricity usage reported in the mean difference tables is pre-trial data and the graphs are from during the Program. Thus it appears that the treatment groups have increased their usage as a result of the Program. This fact provides further motivation to consider habit formation models.

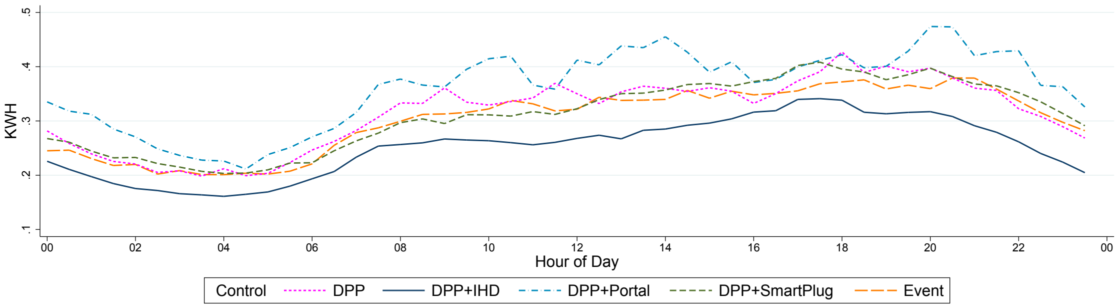

Figure 4.27: Comparison to DPP on 2013-12-14

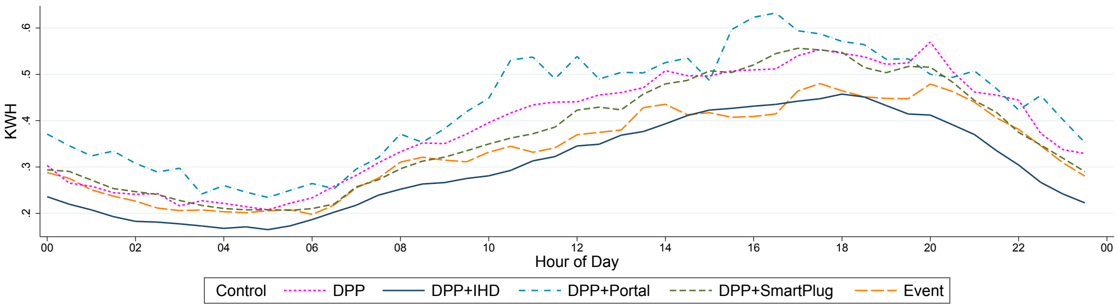

Figure 4.28: Comparison to DPP on 2014-02-02

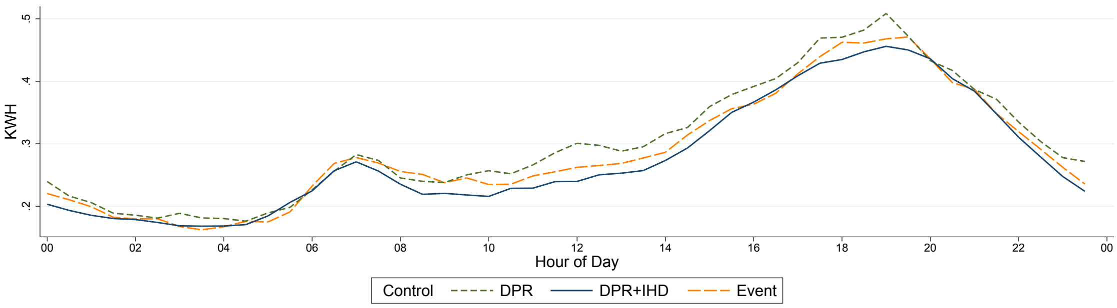

Figure 4.29: Comparison to DPR on 2013-03-26

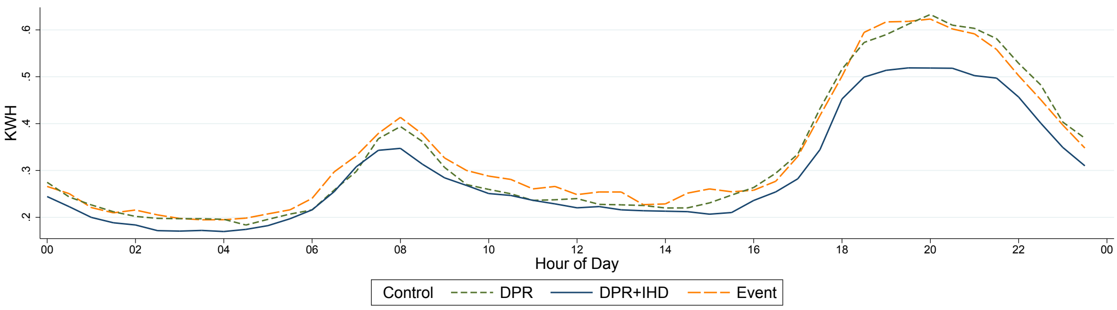

Figure 4.30: Comparison to DPR on 2013-08-15

Chapter 5

Models and Results

In this chapter I consider a range of models which describe households' behaviour during peak price events. I then extend these models to analyse behaviour outside peak price events.

5.1 Electricity Usage

Consider the following difference-in-differences model:

$$ln(kWh)_{it} = \sum_{g} \sum_{p \in (DPP,DPR)} \beta_{g,p} D_{i,t}^{g,p} + \sum_{g} \gamma_g G_i^g + \sum_{p \in (DPP,DPR)} \theta_p E_t^p + u_{it}, \quad (5.1)$$

where $ln(kWh)$ is the natural log of energy usage, measured in kWh, for household i in the 30-minute interval t. The treatment effect is given by $D_{i,t}^{g,p}$ which is equal to 1 if household i is in treatment group g, and if a peak pricing event p occurs for household i in interval t. This model also includes treatment group variables, G_i^g, and two peak pricing event indicators, E_t^p, which equal 1 during peak price event p.

The second model I consider adds time fixed effects to model (1):

$$ln(kWh)_{it} = \sum_{g} \sum_{p \in (DPP,DPR)} \beta_{g,p} D_{i,t}^{g,p} + \sum_{g} \gamma_g G_i^g + \delta_t + v_{it}. \quad (5.2)$$

Time fixed effects, δ_t, include a dummy variable for every 30-minute interval throughout the Program. Thus there are over 42,000 time fixed effects. The variables $\sum_{p \in (DPP,DPR)} \theta_p E_t^p$ do not appear in this model since the two dummies are absorbed by time fixed effects. By having a unique time fixed effect for every half hour window, I can control for variations in weather and lifestyle that may be correlated with the treatment effect. For example, on a very hot day households in all treatment groups would use more electricity than on average. Time fixed effects ensure that the increase in electricity usage for this particular time period is accounted for and does not bias the estimates of the treatment effect.

The third model I consider adds household fixed effects to model (1):

$$ln(kWh)_{it} = \sum_{g} \sum_{p \in (DPP,DPR)} \beta_{g,p} D_{i,t}^{g,p} + \sum_{p \in (DPP,DPR)} \theta_p E_t^p + \alpha_i + w_{it}. \tag{5.3}$$

The term α_i captures household-specific factors that do not vary over time but will influence electricity usage. These could include factors such as usage of devices left in standby mode, whether occupants are home during the day and if the household has gas hot-water heating (provided these factors do not change during the trial period). The household fixed effect term accounts for which treatment group a household is assigned to. This is because the treatment group is time invariant and captured in α_i, thus G_i^g is no longer needed.

The fourth model I consider includes both time and household fixed effects:

$$ln(kWh)_{it} = \sum_{g} \sum_{p \in (DPP,DPR)} \beta_{g,p} D_{i,t}^{g,p} + \delta_t + \alpha_i + e_{it}. \tag{5.4}$$

This model controls for more factors that affect electricity usage than the previous three, since it includes both the fixed effects. The time-invariant differences of each household and aggregate half hourly behaviour are captured in this model. The coefficients $\beta D_{g,p}$ are identified from variations within the households over time.

The fifth model I consider includes both time fixed effects, that vary by LGA, and household fixed effects:

$$ln(kWh)_{it} = \sum_{g} \sum_{p \in (DPP,DPR)} \beta_{g,p} D_{i,t}^{g,p} + \delta_t * LGA + \alpha_i + \epsilon_{it}. \tag{5.5}$$

This model changes the time fixed effects to $\delta_t * LGA$ to allow for a different time fixed effect for each LGA. Given that the weather may differ by LGA and thus each LGA's electricity usage would differ on average at any given time. As a result there are over 567,000 time fixed effect terms. The interpretation is similar to Model (4) but now I am controlling for aggregate half hourly shocks separately for each day and LGA. This model is my preferred model since it controls for the largest number of factors that affect electricity usage, allowing for the most accurate estimation of households responses to dynamic peak price events.

Table 5.1 contains the relevant variables from the first five models with Appendix B containing the full results of all models. Column 1 contains the results of the simple difference-in-differences model, column 2 includes time fixed effects and column 3 includes household fixed effects, column 4 contains both time and household fixed effects, finally column 5 includes the time fixed effects that vary by LGA and household fixed effects.

The estimates of the interaction between treatment groups and the peak price events are relative to those households who did not participate in the peak price event. They act as a control for the households taking part in the event, thus this is a difference-in-difference type comparison.

The coefficients report the average percentage change in electricity usage from assignment to treatment during pricing events. In all models the coefficients are statistically significant at the 1% level. Furthermore the estimated coefficients do not change radically between models. Since the inclusion of time and household fixed effects does not drastically alter the magnitude of the coefficients, this provides further evidence of the integrity of the randomisation.

In the preferred model (column 5) it can be seen that households on a DPP tariff with no feedback technology reduce their usage by approximately 29%. When households have a DPP tariff with a feedback device the effect increases in magnitude to between 29% and 34% depending on the technology. Households with only a DPR tariff reduce usage by 11% on average but by only 8% when combined with an IHD.

Table 5.1: Peak Event Models

	(1)	(2)	(3)	(4)	(5)
$\text{Group}_{DPP-only}$*Event_{DPP}	-0.270***	-0.303***	-0.273***	-0.299***	-0.292***
	(0.038)	(0.038)	(0.038)	(0.037)	(0.039)
$\text{Group}_{DPP+Portal}$*$\text{Event}_{DPP}$	-0.267***	-0.303***	-0.261***	-0.289***	-0.321***
	(0.045)	(0.045)	(0.044)	(0.044)	(0.045)
$\text{Group}_{DPP+Portal+Plug}$*$\text{Event}_{DPP}$	-0.283***	-0.323***	-0.275***	-0.308***	-0.290***
	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)
$\text{Group}_{DPP+IHD}$*Event_{DPP}	-0.225***	-0.267***	-0.232***	-0.267***	-0.337***
	(0.026)	(0.026)	(0.025)	(0.026)	(0.029)
$\text{Group}_{DPR-only}$*Event_{DPR}	-0.112***	-0.112***	-0.121***	-0.121***	-0.113***
	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)
$\text{Group}_{DPR+IHD}$*Event_{DPR}	-0.077***	-0.080***	-0.086***	-0.087***	-0.078***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Time FE	No	Yes	No	Yes	Yes
Household FE	No	No	Yes	Yes	Yes
Adjusted R^2	0.016	0.090	0.357	0.431	0.438
Number of Obs. (mill)	195	195	195	195	195
Number of HHs	7612	7612	7612	7612	7612

Notes: The dependent variable is $ln(kWh)$ in 30-minute intervals. All specifications include a treatment group indicator, interaction between treatment group and a DPP event, interaction between treatment group and a DPR event and two event window indicators (except where subsumed by time or household fixed effects). Standard errors in parentheses are clustered at the household level.

***Significant at the 1% level

**Significant at the 5% level

*Significant at the 10% level

The reductions in electricity usage for the DPP treatment groups with technology are only a few percentage points larger than the DPP-only group, highlighting that technology appears to have a smaller effect than in several other studies. It may not be the case that technology is ineffective but rather that the estimated effect of the peak price event for the DPP-only group is large. Many studies estimate a much smaller effect of a peak price event for treatment groups without technology, usually between 0% and 20%, whereas I estimate a reduction of nearly 30%. Faruqui and Sergici (2011) found that households without technology only decreased usage by 20% but with feedback technology reduced their usage by 32.5%. Herter et al. (2007) found that households without technology reduce usage by 13% but with feedback technology (similar to an IHD) this increased to 41%. Thus the estimated reduction in electricity usage in model (5) for the DPP-only treatment group is larger than what has been estimated in previous studies. One explanation for this is that the large price increase of more than 1200%[1],is driving households to greatly reduce their electricity usage, even when they cannot accurately observe it via feedback technology.

The feedback technology (Portal, Portal+Plug and IHD) all produce similar reductions in usage during peak price events for the DPP groups. This suggests that no technology is overwhelmingly more effective at encouraging households to reduce usage. The smart plug is found to be the least effective technology. Since the smart plug is combined with the online portal it is surprising that is producers a smaller decrease in electricity usage (-0.290) than the portal alone (-0.321). One explanation is that households with a smart plug are content to reduce their electricity usage by a smaller amount during peak price events since they can more easily manage their electricity usage during non-peak event times.

In all models, the coefficients on the DPP event dummies for each treatment group with a DPP tariff are larger in magnitude than the coefficients on the corresponding DPR terms. Hence households with the DPP tariff are estimated to respond more to the peak price events than those on the DPR tariff. This is further supported by a hypothesis test that rejects the null of equality of the DPR coefficients and the corresponding DPP coefficients. For example, the null that the DPP-only group reduce their usage by the same amount and the DPR group is rejected.

These results are in line with an analysis of this data conducted by Frontier Economics (2014). Frontier use a different methodology whereby they estimate the treatment groups usage had a peak event not been called. They do this for each event and find the average reduction for the groups to be 22% for the DPP only

[1]Typically price increases are between 100% and 500%

group, between 20 and 24% for DPP groups with feedback technology, 18% for the DPR group and only 14% for the DPR group with an IHD.

Frontier's findings are similar to those in Table 5.1 in that the DPR group has a greater reduction in usage than the DPR group with an IHD. One explanation is that households with an IHD can accurately view their consumption in real time. The households with an IHD realise how much they have reduced their usage compared to usual and might decide that a smaller reduction than the DPR only group is sufficient. An additional factor that complicates these results is the lack of transparency in the rebate calculations. Households were not told exactly how the rebates were calculated and thus had to decide how much to reduce their electricity usage without knowing the exact baseline they were being compared to.

The problems with the rebate formulation in Wolak (2006) also exist in this trial. Firstly, the rebate calculation provides a strong incentive for households to increase their consumption during peak-periods on non-DPP days. This is so that on DPP days households do not have to reduce their usage as much to receive the same rebate amount. Secondly, the rebate mechanism guarantees that a customer's monthly bill does not exceed what the customer would pay under the ToU or flat tariff. Thus many customers may decide to ignore the peak price event and continue to use electricity as usual, since there is no penalty attached. On a very hot day household may decide to forgo the rebate and continue to use their air conditioning, since they view the rebate as "free" money. These two factors could explain why households in the DPR groups do not reduce their usage as much as the DPP groups.

5.2 Load Shifting

I now consider whether households shift their electricity usage on peak event days away from the more expensive peak time to the relatively cheaper non-peak times. Consider the following model:

$$\begin{aligned} ln(kWh)_{it} = &\sum_{g} \sum_{p \in (DPP,DPR)} \beta_{g,p} D_{i,t}^{g,u} + \sum_{g} \sum_{u \in (DPP-4,DPR-4)} \mu_{g,u} M_{i,t}^{g,u} \\ &+ \sum_{g} \sum_{v \in (DPP+4,DPR+4)} \nu_{g,v} N_{i,t}^{g,v} + \delta_t * LGA + \alpha_i + \epsilon_{it}. \end{aligned} \tag{5.6}$$

This model extends model (5) by including the terms $M_{i,t}^{g,u}$ and $N_{i,t}^{g,v}$ which are a set of dummies for two hours prior (four half hour periods) and two hours post a peak price event. These two sets of variables allow for the detection of load shifting by capturing the increase or decrease in usage for a particular treatment group relative to the control group. For example, if households increase their electricity consumption by turning up their air conditioning prior to an event on a hot day, then we would expect μ to be positive. Similarly after an event the household might turn their air conditioning back up in an attempt to cool their dwelling down, thus we might expect ν to be positive. An alternative possibility is that households might decrease their usage prior to an event so that they are "ready" in advance. Table 5.2 contains the results of this model.

Table 5.2: Load Shifting Model

Variable	Load Shifting Model
2hrs Pre-Event*Group$_{DPP-only}$	-0.003 (0.010)
2hrs Pre-Event*Group$_{DPP+Portal}$	0.028$*$ (0.014)
2hrs Pre-Event*Group$_{DPP+Portal+Plug}$	0.008 (0.017)
2hrs Pre-Event*Group$_{DPP+IHD}$	0.046$***$ (0.009)
2hrs Pre-Event*Group$_{DPR-only}$	$-0.017**$ (0.006)
2hrs Pre-Event*Group$_{DPR+IHD}$	-0.012 (0.007)
2hrs Post-Event*Group$_{DPP-only}$	-0.002 (0.010)
2hrs Post-Event*Group$_{DPP+Portal}$	0.032$*$ (0.014)
2hrs Post-Event*Group$_{DPP+Portal+Plug}$	0.013 (0.014)
2hrs Post-Event*Group$_{DPP+IHD}$	0.049$***$ (0.009)
2hrs Post-Event*Group$_{DPR-only}$	$-0.016**$ (0.006)
2hrs Post-Event*Group$_{DPR+IHD}$	-0.011 (0.007)
Adjusted R^2	0.438
Number of Obs. (mill)	195
Number of HHs	$7,612$

Notes: The dependent variable is $ln(kWh)$ in 30-minute intervals. This specification included time by LGA and household fixed effects. Standard errors in parentheses are clustered at the household level.
***Significant at the 1% level
**Significant at the 5% level
*Significant at the 10% level

The treatment groups with a DPP tariff either increase their usage by a small amount or do not change their usage relative to the control group. This is probably due to households attempting to cool down their house prior to the event. The DPR-only treatment group, decrease their usage prior to an event, however the decrease is less than 2% which is not economically significant.

After a peak event the treatment group responses are nearly identical to their pre-event responses. This symmetry was mentioned when discussing the graphs in the Graphical Analysis section. DPP treatment groups again increase their usage of electricity or do not respond and the DPR only treatment group slightly lower their usage.

Overall there seems to be little evidence of load shifting and those groups that do load shift alter their usage by less than 5%. One of the few comparable studies that considers load shifting is Wolak (2006). He finds there is no evidence of load shifting to any surrounding periods for DPR treatment groups. Jessoe and Rapson (2014) also consider load shifting. They find no evidence of the DPP-only group load shifting but the treatment group with a DPP tariff and an IHD does exhibit load shifting. This group decreased their usage by 10% on either side of a peak price event.

Perhaps the reason that Jessoe and Rapson (2014) find evidence load shifting in one of their treatment groups, is that households who have been notified of the event switch off their devices in advance, so as not to forget. However in Australia we would expect on an extremely hot or cold day households on average would increase usage both before and after a peak event, due to air conditioning. The combination of these conflicting factors may explain why there is little evidence of load shifting in this study. The weather on hot days in Connecticut, USA is around 10 Degrees Celsius cooler and could explain this change in observed behaviour. Households in Australia are much more likely to need the air conditioning on immediately before and after a peak price event so that they can attempt to stay cool during the Summer events. When comparing the results in this thesis to Jessoe and Rapson (2014) it is important to take this into account.

5.3 Habit Formation

I now analyse whether after experiencing multiple events households form electricity usage habits. I remove the peak event days and weekends and estimate the following specification:

$$ln(kWh)_{it} = \alpha + \sum_{g}\sum_{HoD} \lambda_{g,hod} * D_i^g * t * HoD_t + \delta_t + \alpha_i + e_{it} \tag{5.7}$$

The model includes the two fixed effects terms as before but due to restrictions based on the number of observations and computing power, I only use time fixed effects (not interacted with LGA). The new term $\sum_{g}\sum_{hod} \lambda_{g,hod} * D_i^g * t$ is comprised of D_i^g, a treatment group indicator; t, a running variable counting the number of days since a household experienced their first peak price event; and HoD_t, a set of binary variable indicating each hour of the day between 1200 and 2000. Thus $\lambda_{g,hod}$ allows the estimation of a trend for each hour of the peak period by treatment group g.

I hypothesise that households experience a peak event, and alter their behaviour by either increasing or decreasing their electricity usage. Additionally a linear, quadratic or cubic pattern of behaviour could emerge. These habits come about as households receive a large price shock (the peak price event) and consequently change their electricity usage patterns for some amount of time. Another possibility is that a household experiences a peak event, decreases their usage but then slowly revert back to their old behaviour of consuming more electricity, until the next peak event where they then repeat this behaviour. I refer to this as a resetting trend, since the trend term t reverts back to one after each peak price event day that a household experiences. I allow for either a linear or quadratic resetting trend. In the case of a quadratic trend I hypothesise that the household might decrease their usage but at a decreasing rate as they "forget" the last peak price event.

In order to test for these different relationships I run five different models. Each model modifies the trend term t slightly. Table 5.3 summarises the trend terms included in each model and presents the AIC and BIC. AIC stands for Akaike's information criterion and is defined as AIC $= -2\ln L + 2k$ where $\ln(L)$ is the maximized log-likelihood of the model and k is the number of parameters estimated. BIC stands for Schwarz's Bayesian information criterion and is defined as BIC $= -2\ln(L) + k\ln(N)$ where N is the sample size.

Table 5.3: Habit Formation Models

	Linear	Quadratic	Cubic	Resetting Linear	Resetting Quadratic
AIC	3.00582	3.00564	3.00582	3.00591	3.00585
BIC	3.00584	3.00567	3.00583	3.00592	3.00587

These results indicate that the quadratic model is the best fit according to both the AIC and BIC, since this minimises their values. Additionally the quadratic trend model has all trend terms statistically significant. Rather than presenting several pages of statistical tables, I graph the predicted trends in electricity usage for a year based on the statistical tables for the hours 1300 to 1600. The full results are in Appendix B. I present graphs of the quadratic trend term, by hour of day, for the year following a households' first peak event (Figures 5.1 - 5.4).

The DPP, DPP+Portal and DPP+IHD treatment groups generally increase their usage for the first 6 months of the year but then begin to decrease their usage, for each hour of the day. The DPP+Plug group tends to steadily increase their usage for each hour of the day. The magnitudes of the accumulated reductions are very close to zero or are slightly negative after one year for the DPP only, DPP+Portal and DPP+IHD groups. The DPP+Plug group tends to increase electricity usage, relative to the control group, by around 20% for each hour of the day. This increase in usage is of a similar magnitude but opposite in sign to what was found by Jessoe and Rapson (2014). They estimate a 14% accumulated decrease in usage over a two month period by hour of day. Over the equivalent two month time-frame the DPP treatment groups increase usage by about 7.5% and the DPR treatment groups increase usage by around 1%.

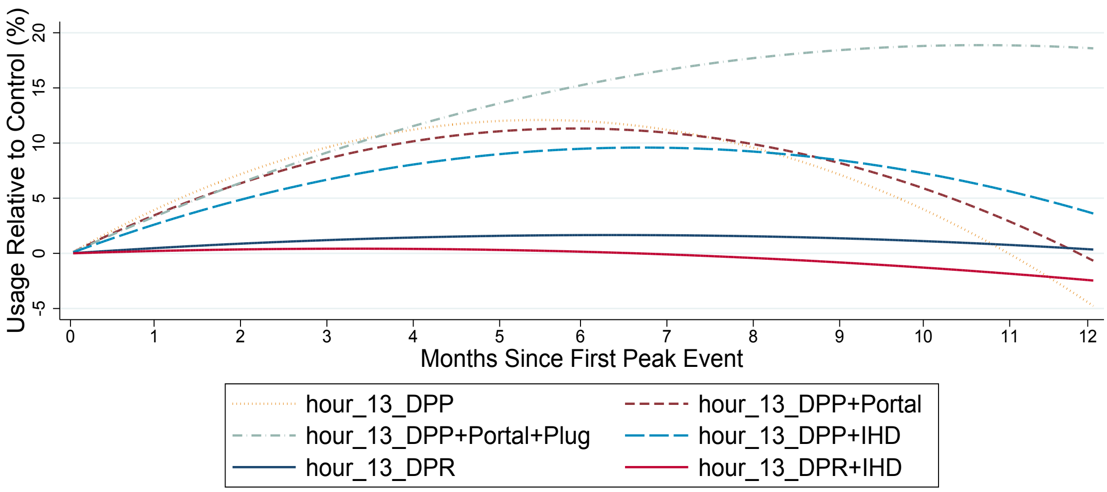

Figure 5.1: Quadratic Trend for Hour 1300

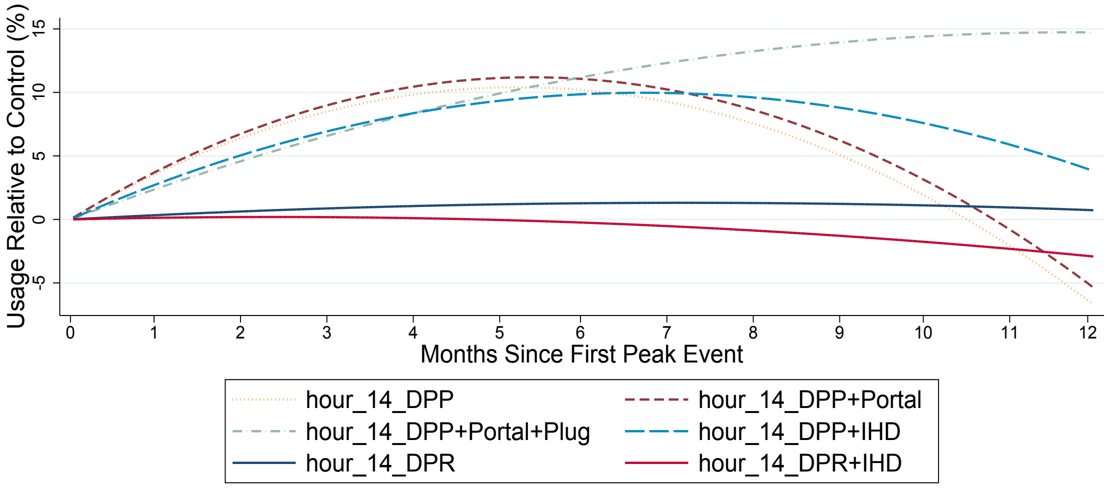

Figure 5.2: Quadratic Trend for Hour 1400

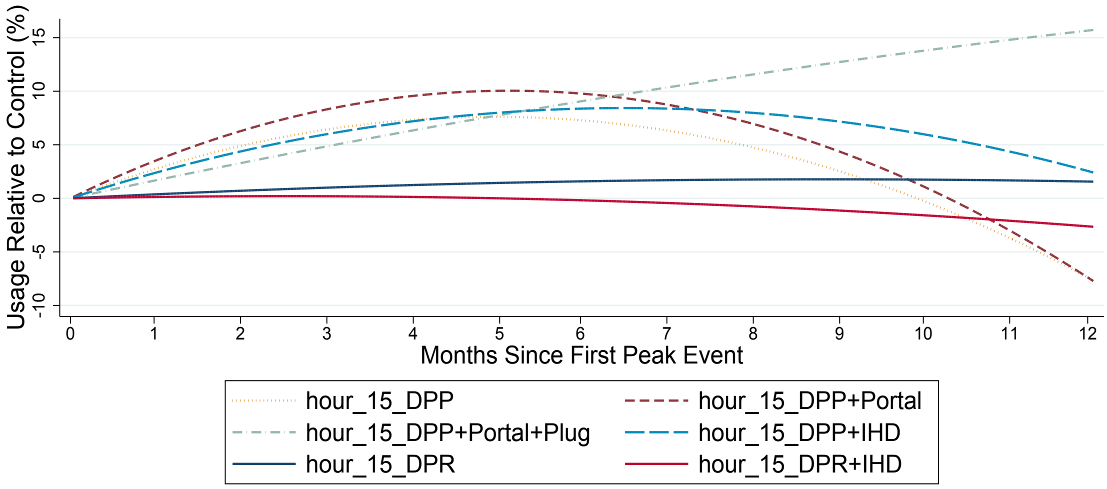

Figure 5.3: Quadratic Trend for Hour 1500

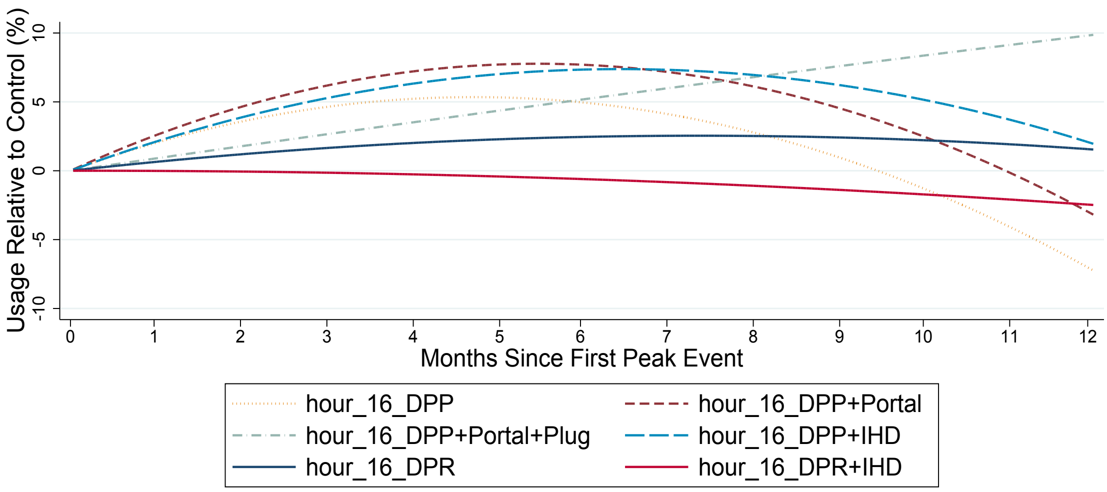

Figure 5.4: Quadratic Trend for Hour 1600

There are some issues with this model though which may explain the difference in results. Firstly unlike Jessoe and Rapson (2014) the DPP households did not begin the Program all at the same time. As discussed in Chapter 4 households were progressively added to the Program. The first two DPP events had a small number of households (400) and the third event was not until 8 months later. Thus this model is assuming that the habits of the 400 households that participated in the first two events are the same as those households that joined the Program later and experienced their first peak event in November 2013.

Secondly the households that joined the Program later experienced a rapid succession of peak events, thus the habits they form could be vastly different to those formed by households who experienced the first two events. Of course the model is appropriate if we are willing to accept that the frequency and spacing of events has no effect on habits. This model assumes that it is the peak event that triggers the households change in behaviour and consequently they form habits.

Now an alternative model which is less restrictive is considered. I create one sub-sample of the DPP treatment groups and two sub-samples of the DPR treatment group as shown in Figures 5.5 and 5.6. I take the 4 months following the peak event on 22 March 2013 for the DPP groups and analyse their behaviour. Since there are no peak events in this period it is representative of how households might behave in Spring and Autumn, relative to the control group, when no peak events are usually called.

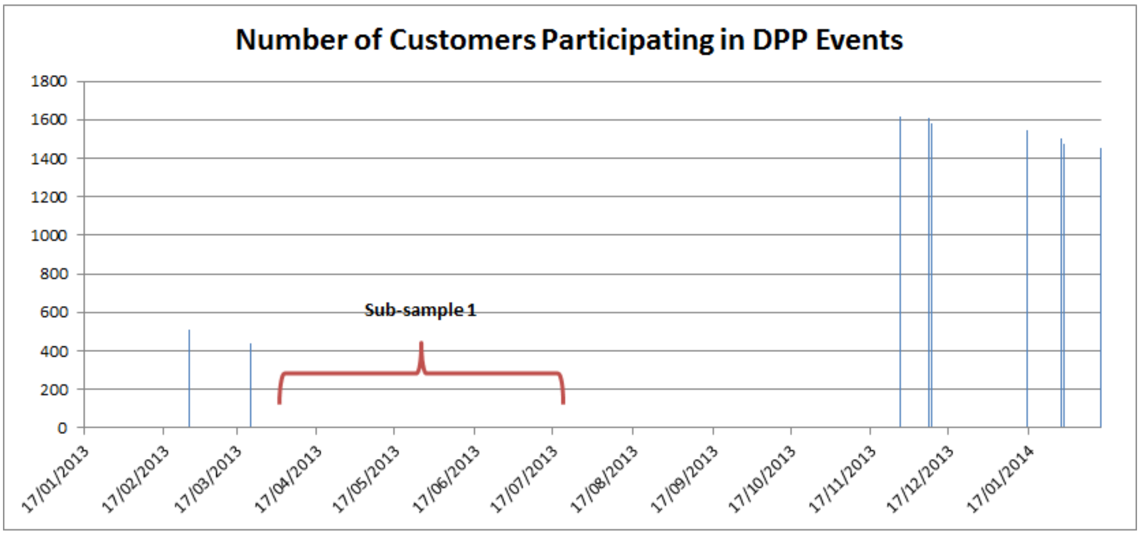

Figure 5.5: DPP Sub-sample

For the DPR groups I take the 4 months after 28 March 2013 (sub-sample 1) and 22 August 2013 (sub-sample 2) and analyse whether any habits are formed over these two periods. This new model does not assume households behave the same

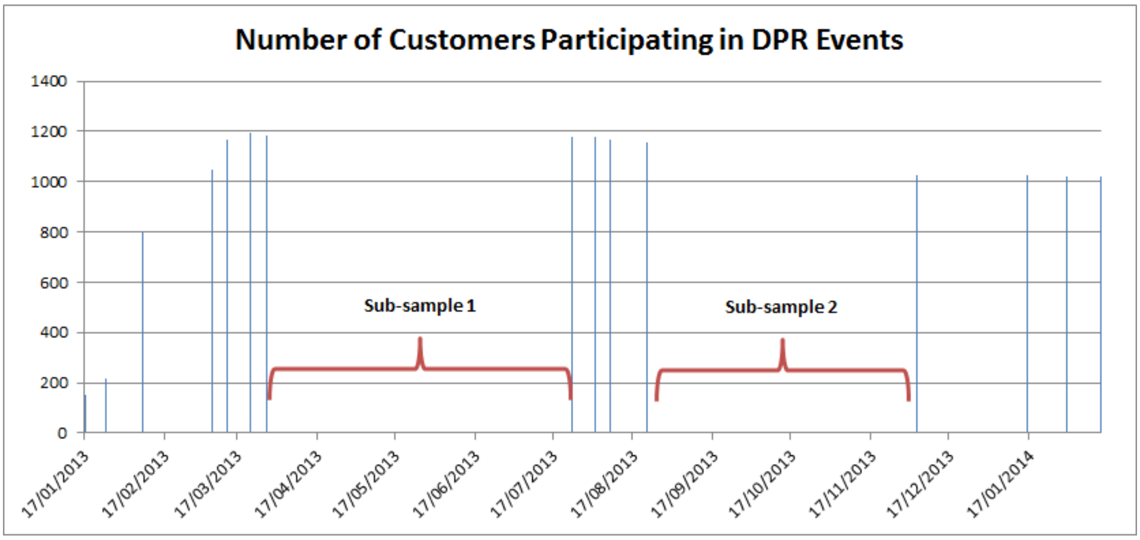

Figure 5.6: DPR Sub-sample

way regardless of the interval between peak events, since it considers only periods after peak events cease. This model aims to determine if households change their behaviour relative to the control group once they cease to experience peak events for a few months, as may be the case in Spring and Autumn.

I use statistical significance tests, AIC and BIC to compare different trend models and find that a linear trend is optimal for the DPP treatment groups as well as the DPR treatment groups. The tables of results are presented in Appendix B, see Table B.8 - B.10. I present the results graphically instead to best illustrate the trends. The DPP results are all statistically significant and Figures 5.7 - 5.10 show that after 4 months of no peak events, households increase their usage by 20%-30%. These estimates are larger than those in the in the previous model. In order to have a fair comparison I consider the linear trend in the previous model. The results in Appendix B suggest that households increase their electricity usage by much more during a break in peak events. This is because the break model is estimated over a shorter time frame and separates out the effects due to peak events ceasing. It supports the hypothesis that households begin to increase their usage if peak price event stop for a period of time.

Figures 5.11 - 5.14 show the DPR treatment groups change in electricity usage relative to the control group from 29/3/2013 until 30/7/2013 during the peak hours of the day and Figures 5.15 - 5.18 show the DPR treatment groups change in usage from 22/8/2013 until 26/11/2013 relative to the control group. In the first sub-sample DPR households increase their usage, but by much less than the DPP households over the same period of time. This could be because the DPR households experienced more events prior to the break in treatment (Some DPR households experienced 7 events rather than 2). Alternatively this behaviour could be because the DPP households greatly reduced their usage after the peak event and are slowly returning back to their prior usage patterns.

Interestingly in sub-sample 2 when DPR events cease, households on a DPR tariff actually decrease their usage, though many of the coefficients are not statistically significant. The results provide an interesting insight into households' behaviour. After the initial series of peak events for the DPR treatment groups they increase their usage. However after a second series of peak events they begin to decrease, or at least stop increasing their usage. It appears households are learning through the series of peak events and changing their behaviour as a result.

These results have important policy implications since if households are using less electricity in the longer run, then a DPP or DPR tariff could be considered as a means of reducing greenhouse gas emissions. Ideally these households would be monitored for another year to ensure that the households continue to reduce their electricity usage, or at least do not increase their usage, relative to the control group.

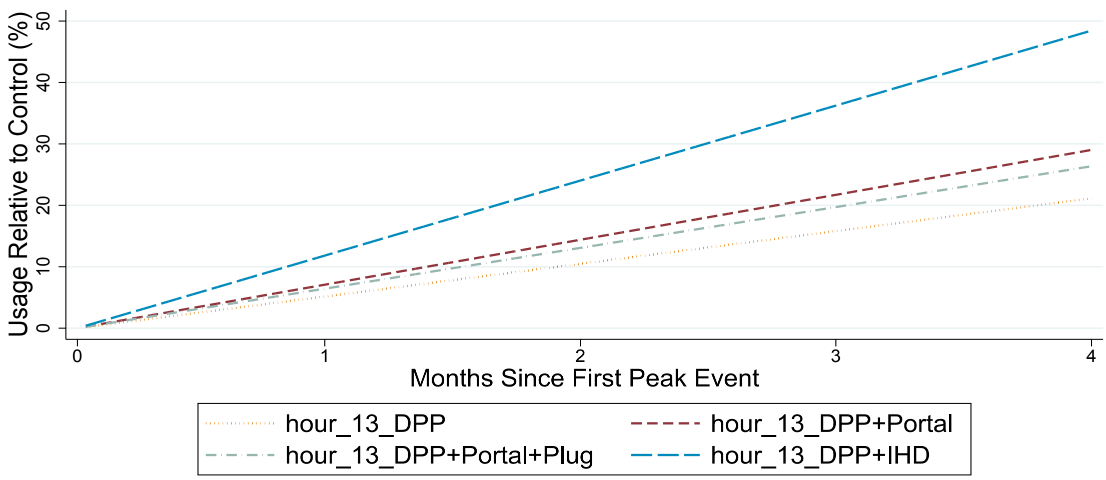

Figure 5.7: DPP Trend for Hour 1300

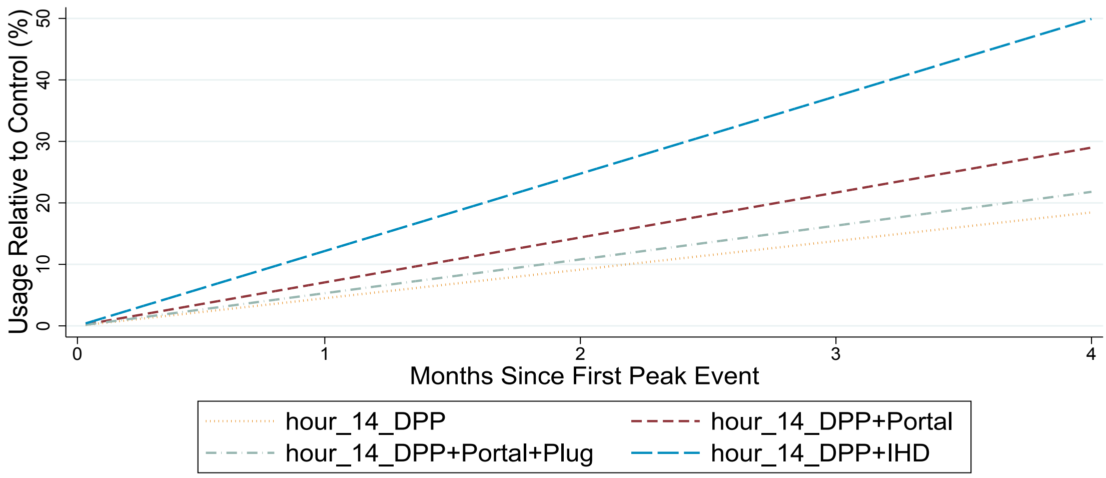

Figure 5.8: DPP Trend for Hour 1400

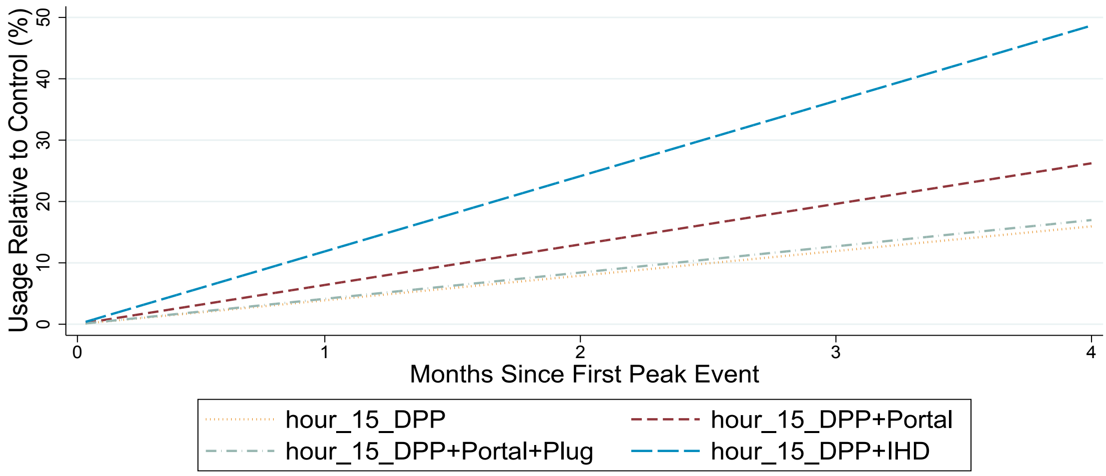

Figure 5.9: DPP Trend for Hour 1500

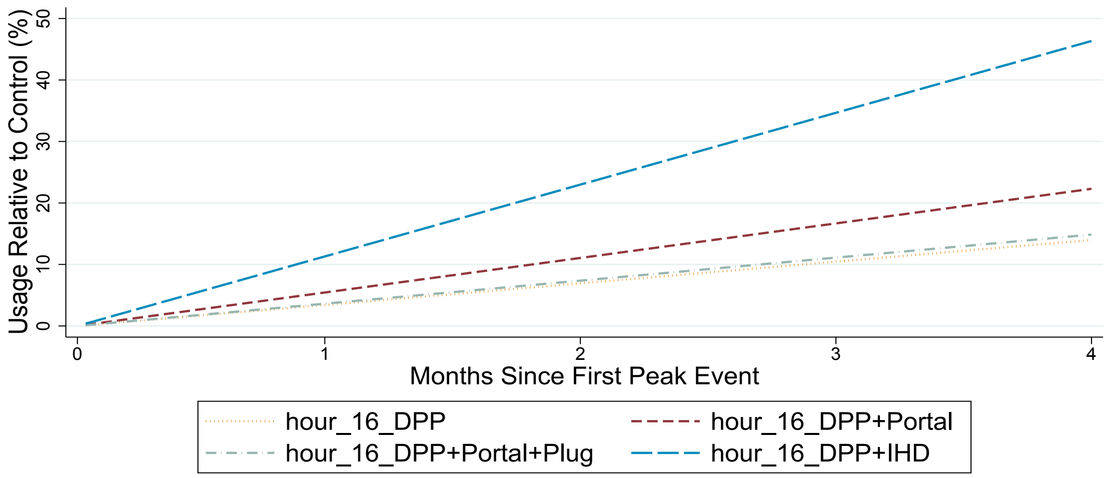

Figure 5.10: DPP Trend for Hour 1600

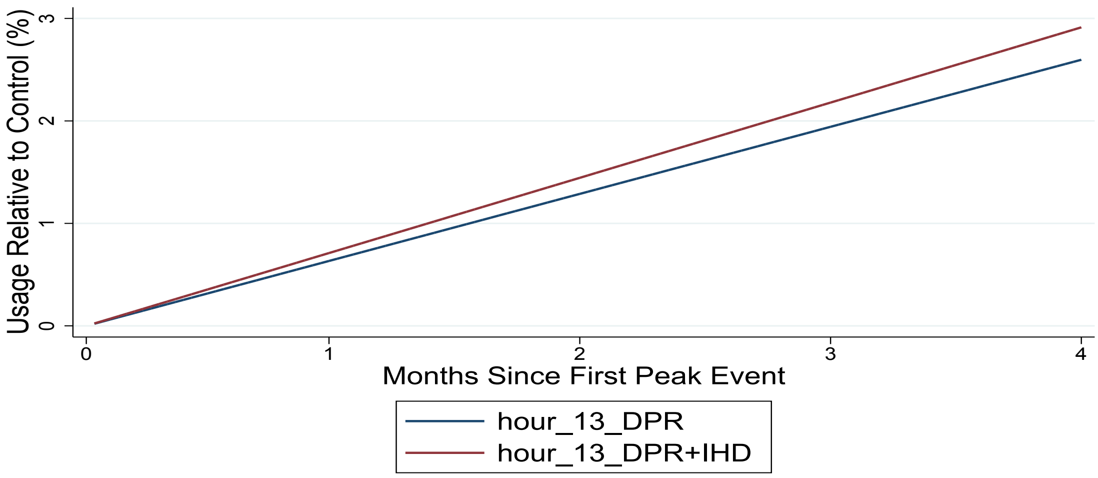

Figure 5.11: DPR1 Linear Trend for Hour 1300

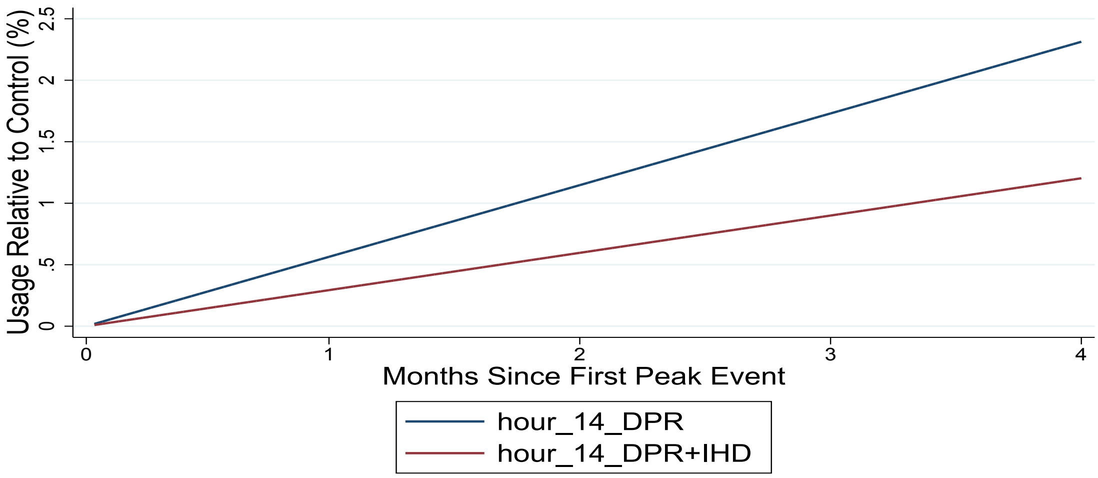

Figure 5.12: DPR1 Linear Trend for Hour 1400

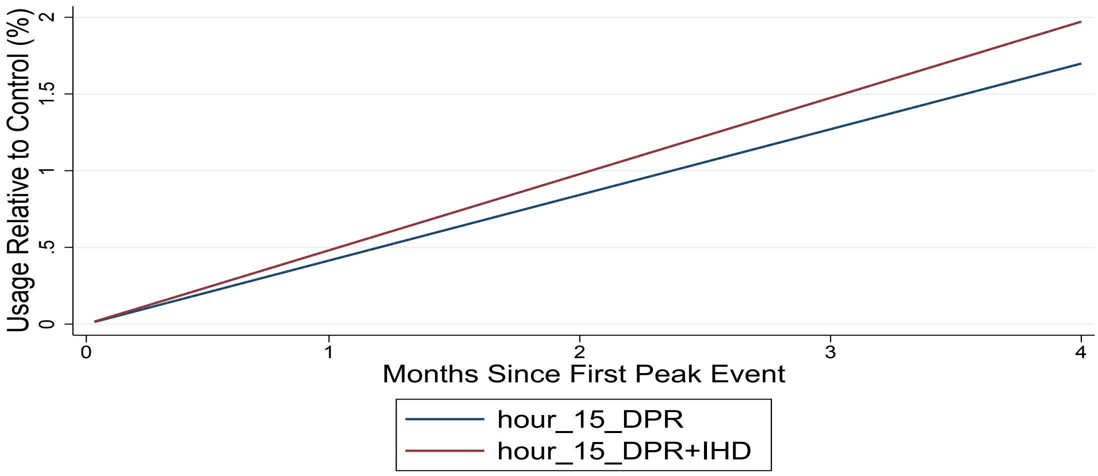

Figure 5.13: DPR1 Linear Trend for Hour 1500

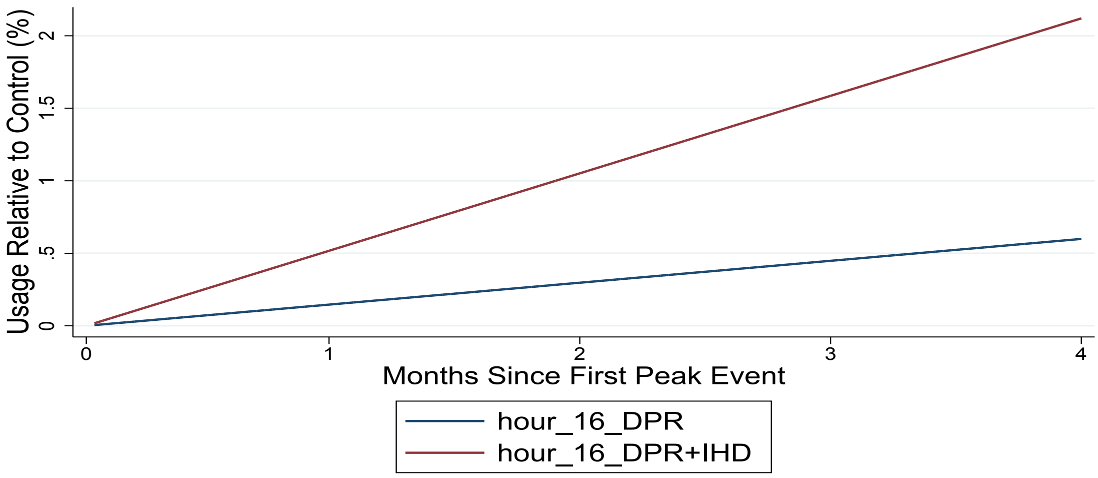

Figure 5.14: DPR1 Linear Trend for Hour 1600

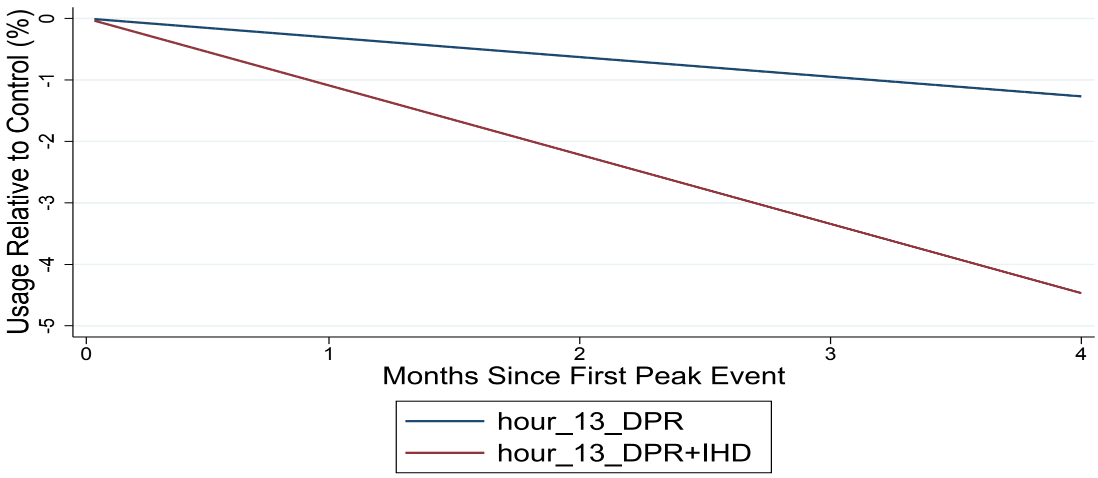

Figure 5.15: DPR2 Linear Trend for Hour 1300

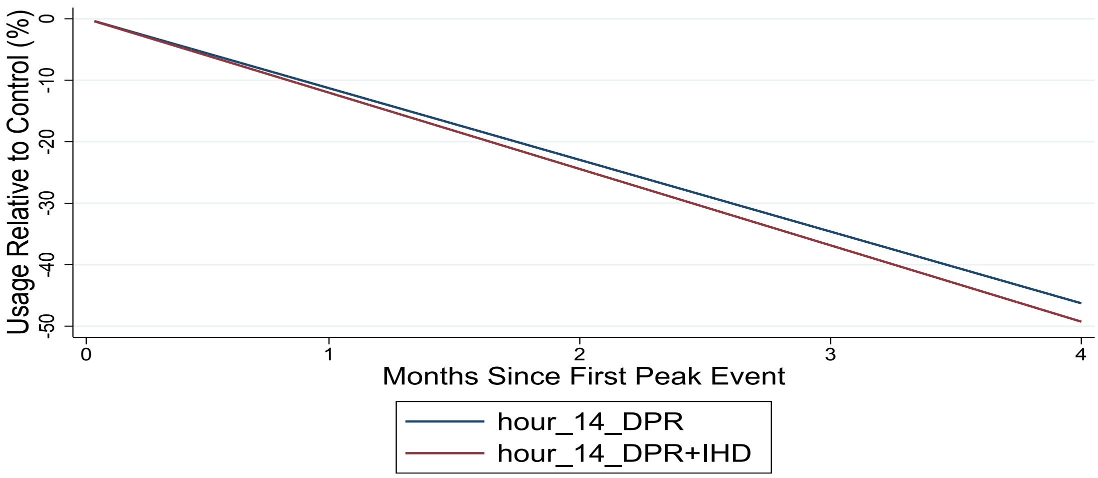

Figure 5.16: DPR2 Linear Trend for Hour 1400

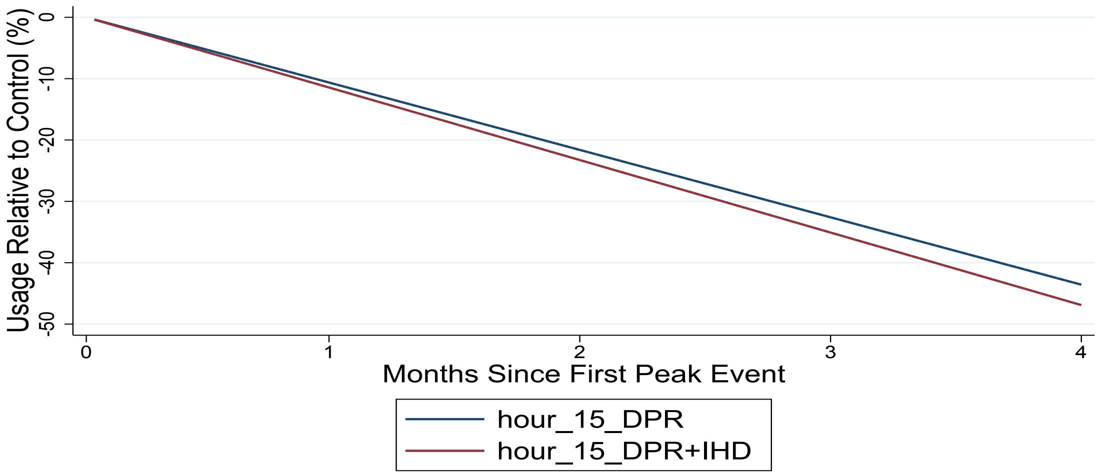

Figure 5.17: DPR2 Linear Trend for Hour 1500

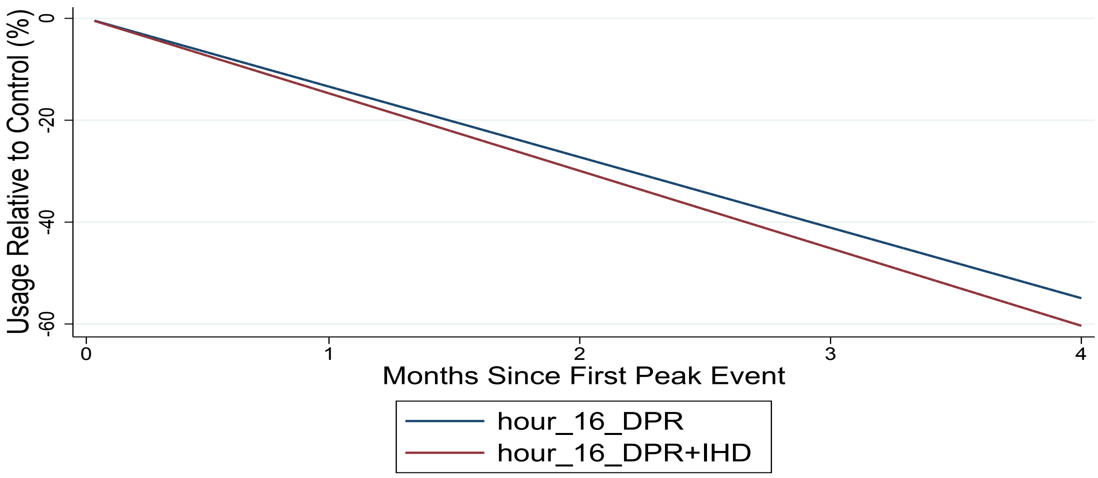

Figure 5.18: DPR2 Linear Trend for Hour 1600

Chapter 6

Further Issues

In this chapter I perform robustness checks to validate the data and results found in the previous chapters. I construct a placebo test, analyse attrition and discuss the external validity of the results.

6.1 Placebo Test

There are several explanations for the observed reduction in electricity usage during peak events. One could argue households would have behaved this way regardless of a dynamic peak event occurring. It is possible that households in the treatment group always decide to turn their air conditioning off during the peak hours of the day (perhaps if they are not at home) and thus the estimated treatment effects are incorrect. To test the hypothesis that households in treatment groups that experience peak events reduce their usage at peak times on all days, I construct a placebo test. The model is as follows:

$$ln(kWh)_{it} = \sum_g \beta D^g_{i,DPP-336} + \sum_g \beta D^g_{i,DPR-336} + \delta_t * LGA + \alpha_i + \epsilon_{it}. \tag{6.1}$$

The terms $\sum_g \beta D^g_{i,DPP-336}$ and $\sum_g \beta D^g_{i,DPR-336}$ are equal to one, exactly one week earlier (336 half-hour periods earlier) than the dynamic peak event was scheduled for. By formulating the model in this manner it ensures that the same days of the week are being compared and that any habits dependent on the day of week are accounted for. Table 6.1 contains the results of the placebo test for all the standard peak event models. To conserve space I present only the coefficients of interest, for full results see Table B.7 in Appendix B

Table 6.1: Placebo Test

Main Models	(1)	(2)	(3)	(4)	(5)
$\text{Group}_{DPP-only}$*Event_{DPP}	−0.001	−0.007	−0.003	−0.002	−0.008
	(0.017)	(0.014)	(0.015)	(0.013)	(0.013)
$\text{Group}_{DPP+Portal}$*$\text{Event}_{DPP}$	0.017	0.015	0.024	0.028	0.020
	(0.021)	(0.019)	(0.020)	(0.018)	(0.017)
$\text{Group}_{DPP+Portal+Plug}$*$\text{Event}_{DPP}$	0.007	0.007	0.015	0.022	0.019
	(0.022)	(0.020)	(0.020)	(0.019)	(0.018)
$\text{Group}_{DPP+IHD}$*Event_{DPP}	0.042**	0.043***	0.037**	0.044***	0.032***
	(0.013)	(0.010)	(0.012)	(0.009)	(0.008)
Group_{DPR}*Event_{DPP}	−0.030*	−0.019	−0.030*	−0.019	−0.016
	(0.015)	(0.012)	(0.014)	(0.011)	(0.011)
$\text{Group}_{DPR+IHD}$*Event_{DPP}	−0.026	−0.016	−0.025	−0.015	−0.011
	(0.016)	(0.013)	(0.015)	(0.013)	(0.013)
Group_{Portal}*Event_{DPP}	−0.032*	−0.021*	−0.034**	−0.023**	−0.013
	(0.012)	(0.009)	(0.012)	(0.008)	(0.008)
$\text{Group}_{Portal+IHD}$*$\text{Event}_{DPP}$	−0.025	−0.008	−0.027	−0.010	−0.012
	(0.030)	(0.029)	(0.029)	(0.028)	(0.028)
$\text{Group}_{Portal+Plug}$*$\text{Event}_{DPP}$	−0.015	−0.002	−0.026	−0.013	−0.009
	(0.036)	(0.035)	(0.032)	(0.031)	(0.030)
Group_{IHD}*Event_{DPP}	−0.029	−0.020	−0.033*	−0.022	−0.020
	(0.016)	(0.013)	(0.015)	(0.012)	(0.012)
$\text{Group}_{DPP-only}$*Event_{DPR}	0.025*	0.010	−0.005	−0.006	−0.009
	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)
$\text{Group}_{DPP+Portal}$*$\text{Event}_{DPR}$	0.037**	0.020	0.008	0.004	−0.002
	(0.012)	(0.011)	(0.010)	(0.009)	(0.009)
$\text{Group}_{DPP+Portal+Plug}$*$\text{Event}_{DPR}$	−0.003	−0.023	−0.027	−0.034*	−0.029
	(0.021)	(0.021)	(0.016)	(0.015)	(0.015)
$\text{Group}_{DPP+IHD}$*Event_{DPR}	0.042***	0.022**	0.016*	0.008	−0.003
	(0.009)	(0.007)	(0.008)	(0.006)	(0.006)
$\text{Group}_{DPR-only}$*Event_{DPR}	−0.004	0.000	−0.013	−0.002	−0.001
	(0.008)	(0.007)	(0.008)	(0.006)	(0.006)
$\text{Group}_{DPR+IHD}$*Event_{DPR}	−0.003	−0.003	−0.012	−0.004	−0.003
	(0.009)	(0.007)	(0.008)	(0.007)	(0.007)
Group_{Portal}*Event_{DPR}	−0.003	−0.001	−0.010	−0.001	0.000
	(0.007)	(0.005)	(0.006)	(0.004)	(0.004)
$\text{Group}_{Portal+IHD}$*$\text{Event}_{DPR}$	0.015	0.013	0.009	0.015	0.017
	(0.015)	(0.015)	(0.014)	(0.013)	(0.013)
$\text{Group}_{Portal+Plug}$*$\text{Event}_{DPR}$	−0.049*	−0.038	−0.048**	−0.030	−0.025
	(0.021)	(0.021)	(0.019)	(0.018)	(0.018)
Group_{IHD}*Event_{DPR}	−0.001	0.001	−0.011	−0.001	0.000
	(0.008)	(0.007)	(0.008)	(0.006)	(0.006)
Adjusted R^2	0.016	0.090	0.357	0.431	0.438
Number of Obs. (mill)	195	195	195	195	195
Number of HHs	7612	7612	7612	7612	7612

Notes: The dependent variable is $ln(kWh)$ in 30-minute intervals. All specifications include a treatment group indicator, interaction between treatment group and a DPP event, interaction between treatment group and a DPR event and two event window indicators (except where subsumed by time or household fixed effects). Standard errors in brackets are clustered at the household level.

***Significant at the 1% level

**Significant at the 5% level

*Significant at the 10% level

If households are responding only to a dynamic peak price event then we would expect the coefficients on $\sum_g \beta D^g_{i,DPP-336}$ and $\sum_g \beta D^g_{i,DPR-336}$ to be statistically insignificant. This is because we would not expect the treatment groups to have statistically different usages to the control group a week earlier, at the same time of day as a peak price event occurred. The only variable that has a statistically significant coefficient in the preferred model (5) is Group$_{DPP+Portal+Plug}$*Event$_{DPR}$, however it is not economically significant. It has an estimated coefficient of 3.2% suggesting that at this time the DPP+IHD group was using only a small amount more than the control group. These results suggest that households are responding to the dynamic peak price events and do not exhibit this behaviour every day.

An additional placebo test is already built into the Peak Event Models constructed in Chapter 5. Since all treatment groups are interacted with both DPP and DPR peak price events, then the interaction of a treatment group with an event that the group did not participate in acts as a placebo test. This form of placebo test may be superior since it ensures that extreme days are being used, thus households' behaviour is being compared to a similar type of day. The results are contained in Appendix B. All coefficients on the interaction between DPP groups on a DPR event day, and, DPR groups on a DPP event day are statistically insignificant. Thus the there is strong evidence that households are responding to the peak price events and do not reduce their electricity usage at peak times every day, relative to the control group.

6.2 Attrition

An analysis of attrition is conducted to ensure that households with particular characteristics were not consistently exiting the Program. A reason was recorded for each household when they exited the Program, these included: the Program finished, the occupants moved house and the household wished to opt out of the Program. Of particular interest is if households who opted out had certain characteristics. If a large number of these households opt out during the Program then this will effect the randomness of the remaining sample. Table 6.2 contains the number of households that opted out of the Program for each group, expressed both as a number and percentage of that group.

Table 6.2: Attrition by Treatment Group

	DPP		DPR		None		Total	
	#	%	#	%	#	%	#	%
IHD	136	13	48	7	68	10	252	11
Portal	66	20	0	0	74	6%	140	8
IHD and Portal	0	0	0	0	8	4	8	0
Smart Plug and Portal	23	16	0	0	31	48	54	26
None	77	19	37	5	0	0	114	4
Total	302	16	85	6	181	4	568	7

The smart plug and portal treatment group has the highest attrition rate at 48 percent. Treatment groups with smart plugs were required to have devices manually installed. Thus an installation time had to be arranged by phone and then the household had to pick a time for installation. This more complicated process explains why households may have opted out of the Program. For households on a DPR tariff the opt out rate was very low, 6 percent total. Households on a DPP tariff had a higher drop out rate of 16 percent in total. This can be attributed to some households ending up worse off from the price structure and opting out of the Program. Finally the control group had no participants exit the Program.

To test the sensitivity of the results I run the preferred Peak Event Model (Model 5) omitting households that dropped out of the Program. The results are presented in Table 6.3 and suggest that the reduction in usage differs by only 2% for each treatment group, when the households that dropped out of the Program are removed.

Table 6.3: **Balanced Panel Model**

Variable	(5)
DPP only*DPP-event	-0.309^{***}
	(0.044)
DPP+Portal*DPP-event	-0.345^{***}
	(0.049)
DPP+Plug+Portal*DPP-event	-0.317^{***}
	(0.070)
DPP+IHD*DPP-event	-0.354^{***}
	(0.031)
DPR*DPR-event	-0.120^{***}
	(0.016)
DPR+IHD*DPR-event	-0.085^{***}
	(0.017)
Adjusted R^2	0.439
Number of Obs. (mill)	183
Number of HHs	7044

The results discussed above provide some confidence that attrition is not biasing the results. However many of the households that dropped out did so before any or after only two peak events. It is possible that the households that dropped out early in the Program had particular characteristics, that would have effected the results. This situation is not accounted for in the test above. To address this concern I run a linear probability model (LPM) and a logistic regression of the following form:

$$\begin{aligned}\text{Optout}_i = \sum_a \alpha_a \text{IncomeCategory}_i^a + \sum_b \beta_b \text{GasUsage}_i^b + \sum_c \gamma_c \text{ElecticityUsage}_i^c \\ + \delta \text{DwellingType}_i + \sum_d \zeta_d \text{LGA}_i^d + u_{it},\end{aligned} \tag{6.2}$$

where $\text{Optout}_i = 1$ if household i opts out of the Program, $\text{IncomeCategory}_i = 1$ if household i is in income category a, $\text{GasUsage}_i = 1$ if household i is in gas usage group b, $\text{ElecticityUsage}_i = 1$ if household i is in electricity usage group c, $\text{DwellingType}_i = 1$ if the dwelling is not a unit, $\text{LGA}_i = 1$ if household i is in LGA d.

Tables C.1 - C.6 in Appendix C contain the LPM and logistic regression results. According to the LPM and logistic regression none of the household variables are significant in predicting whether a household will opt-out of the Program. Consequently attrition appears to be of little concern.

6.3 External Validity

The results and observations discussed in the previous chapters are applicable to other trials in Australia and throughout the world. There are a few caveats to this particular Program which I outline below.

In reality it is less likely that a DPR program would be implemented over a DPP program, if smart meters were rolled out on a large scale. This is because the design of the DPR tariff is such that a household can not possibly end up worse off. As a result of the pricing design households have an incentive to increase usage when a peak event is not taking place, in order to increase their rebate during a peak price event. For the rebate to be worthwhile for the electricity suppliers, the supplier's savings would have to exceed the amount they pay out in rebates to households. More realistically an electricity company would charge households a higher price for using electricity in these peak hours. On the other hand the government may see fit to intervene and implement a DPR program, so it is not completely unreasonable to consider a DPR.

The design of the price mechanism for the DPR group may be one explanation for the smaller response of this group compared to DPP groups during peak price events. If a household is only making a few dollars for not using their air conditioning on an extremely hot day, then this may be an insufficient incentive for a household to decrease their electricity usage. A 1200% increase in the price on the other hand, appears to encourage households to decrease their usage.

The mean difference results also suggest a statistical difference in the composition of treatment group based on household demographics. Whilst this is controlled for in the regressions through fixed effects, it still causes some concern. It is possible that since the treatment groups have different demographics to the control group, the treatment effects found are due to household demographics rather than the policy. For example if more households in a treatment group had higher income relative to the control group, then they may be less responsive to peak events. This may cause the results to be biased and incorrect conclusions to be drawn about the effectiveness of the policy. As discussed in the Mean Differences Chapter the differences between control and treatment groups are typically less than 10 percentage points and even lower for reported electricity usage.

The results from this experiment appear to be generally transferable to other parts of Australia and other locations with a warm climate. Whilst the electricity usage and other household demographics may differ for other areas, these factors were controlled for and thus the responsiveness of households should be similar.

Chapter 7

Discussion and Conclusions

There are some limitations of the experiment design that are worth considering for future trials. If a similar experiment were to be conducted households should be signed up to the trial, have a smart meter installed and then be randomly assigned to a treatment group or the control group. By signing all households up at the same time and having them agree to participate before assigning them to a treatment group, this avoids issues with customers declining to participate if assigned a particular product. This would avoid any potential biases from households with particular demographics being more likely to opt-out of the trial.

This study does not account for households who are not home during the day and may have found it harder to schedule an installation appointment for a smart plug device. If occupants who are not home during the day are less likely to respond in a peak event, then the estimated treatment effects may be biased. Thus households best able to respond to price are more likely to be in the Program. However in the case of the smart plug this effect is minimised. Households who are not home during the day can still respond to the peak event when not at home, since users can turn off devices remotely using a smart phone or tablet.

An additional concern hinted at earlier is that households on a DPP tariff, may have been more likely to drop out if their bills were increasing. Thus the sample I am left with has the households that did not experience a drastic bill increase, because they were more responsive at peak times. Since I am interested in how households respond during peak times this is of some concern.

Further work in analysing the effectiveness of DPP tariffs over the long term would be beneficial. Households' responses three years after being placed on a DPP tariff may be different to their responses six months after the tariff. The estimated reductions in electricity usage may increase as households become accustomed to these peak events, or decrease if households decide that the benefit of reducing usage on numerous peak days for an extended period is not worth the cost.

Other extensions could examine households' habit formation in even more detail. Analysing if households' reduce their usage on non-peak days permanently or only for a few months is an important question when considering the benefits of DPP tariffs and smart meters in general. Additionally the Spring and Autumn periods when peak events are not typically called, should be further analysed. These periods constitute a large portion of the year and thus households' actions are important. This is the first study to observe household behaviour in these periods. For the DPR treatment groups I observed an increase in the Autumn period and then a decrease in electricity usage in the Spring period. If this behaviour persists then I would expect households to remain steady in their electricity usage during the seasons with no peak events typically called. Alternatively this pattern could have been due to the seasons, it would be interesting to observe the households' behaviour in the following year at these times.

When I compare my results to those discussed in Chapter 2, the magnitudes are similar. A 29% - 34% reduction in electricity usage for the DPP groups which had feedback technology is similar to many other papers, but a 29% reduction is considered a larger estimate for the DPP-only group. Regardless the technology still enhances households' electricity reduction. Furthermore, load shifting appears to be minimal and thus there is an overall reduction in electricity usage as a result of the DPP and DPR tariffs in the short term, relative to the control group. The fact that households do not load shift is not surprising given the climate in Australia and the findings of a couple of other papers.

Prior to this experiment the effectiveness of dynamic peak pricing had not been analysed on a large scale in Australia. It would be easy to think that dynamic peak pricing would be less effective in a nation known for its warm climate and extreme heat. Since peak events are called on only the most extreme days, when households would usually use their air conditioning, the responsiveness of households is somewhat surprising. The responsiveness could be attributed to the huge price increase of over 1200% during these peak times. Regardless, the fact that this policy works is sufficient to further consider dynamic peak pricing across Australia and other nations.

In summary, I have found that dynamic peak pricing is effective in reducing household electricity usage, as are dynamic peak rebates, albeit to a lesser extent. The fact that dynamic peak pricing is effective in achieving lower household electricity usage warrants further research into the possibility of a large scale smart meter rollout. With the widespread implementation of smart meters and dynamic peak pricing, the marginal cost of electricity for suppliers will be much closer to their marginal revenue. Furthermore households will be able to better monitor their electricity usage, if provided with feedback technology, and have the potential to save money by altering their electricity usage habits. Thus smart meters and dynamic peak pricing have the potential to improve outcomes for both households and electricity suppliers.

Appendices

Appendix A

Additional Research Design Information

A.1 Event Dates and Times

Table A.1: Frequency of DPP Events

Start Time	End Time	Number of Participants
26/02/2013 13:00	26/02/2013 15:00	513
22/03/2013 13:30	22/03/2013 17:30	438
28/11/2013 14:00	28/11/2013 18:00	1615
9/12/2013 14:00	9/12/2013 17:00	1608
10/12/2013 14:30	10/12/2013 16:30	1584
16/01/2014 14:30	16/01/2014 17:30	1543
29/01/2014 15:00	29/01/2014 18:00	1504
30/01/2014 15:00	30/01/2014 18:00	1473
13/02/2014 13:00	13/02/2014 17:00	1451
Grand Total		11729

Table A.2: Frequency of DPR Events

Start Time	End Time	Number of Participants
17/01/2013 12:00	17/01/2013 16:00	150
25/01/2013 13:00	25/01/2013 17:00	217
8/02/2013 13:30	8/02/2013 17:30	800
7/03/2013 11:30	7/03/2013 15:30	1050
13/03/2013 13:00	13/03/2013 17:00	1168
22/03/2013 13:30	22/03/2013 17:30	1192
28/03/2013 11:30	28/03/2013 15:30	1184
24/07/2013 16:30	24/07/2013 19:30	1179

2/08/2013 16:30	2/08/2013 19:30	1176
8/08/2013 16:30	8/08/2013 20:00	1165
22/08/2013 17:00	22/08/2013 20:00	1157
4/12/2013 13:00	4/12/2013 17:00	1024
16/01/2014 13:00	16/01/2014 17:00	1028
31/01/2014 13:00	31/01/2014 17:00	1023
13/02/2014 13:00	13/02/2014 17:00	1021
Grand Total		14534

A.2 Trial Constraints

The final list of all constraints that were placed on the customer selection process for the Network Trial and associated control group were as follows:

1. Within the SGSC local government areas – note that all customers for the Network Trials were selected from the original eight LGAs but for the Retail Trials, an additional fourteen LGAs were required to be used
2. Ausgrid customer class = "Domestic" (i.e. customers who were not charged a business network tariff)
3. Portal compliant meter configuration (i.e. the customer portal was not able to collate and show electricity usage data from all meter configurations – only the most common were catered for)
4. Not chronic access (i.e. where the customer's dwelling was classed by Ausgrid as having meter access issues)
5. Not life support (i.e. where the customer has flagged to Ausgrid that an occupant is dependent on electricity for life support purpose)
6. Not a business, church, club, college, school, government, consulate or any other type of non-domestic premise (i.e. the various customer name and address fields were scanned against a list of 164 terms to remove any obvious nonresidential customers)
7. Not a strata or serviced apartment building

8. Not a Current Transformer (CT) meter (as this type of meter can't be replaced by an SGSC meter)
9. Not house lights for a block of units, etc
10. Not allocated to an SGSC Energy & Resource Management trial
11. Not allocated to an existing Ausgrid (non-SGSC) trial
12. Not staff trial customer
13. Not Smart Home
14. Not permanent disconnection
15. Customer hasn't already dissented
16. Not already checked as poor coverage during a manual walk testing of over 11,000 dwellings
17. Within the anticipated -85 dbm coverage polygon as defined by the WiMAX team
18. Anticipated to have sufficient signal strength using the Google Earth maps with previous successful and unsuccessful SGSC meter installations data plotted
19. Within the anticipated sufficient signal strength areas based on drive tests around some WiMAX towers
20. Within multi-dwelling units (MDUs) that have been qualified as having sufficient signal strength at the meters
21. Within MDUs where the current meter boards will support the larger format SGSC meters
22. Within MDUs where no insurmountable complications such as parking, access, impacts to other Ausgrid customers or customer dissent or any other issues exist
23. Within MDUs where the description of the location of the meter boards does not include the word "basement"
24. Within MDUs where meters that have a type/id combination that reflects a meter board that is compatible with the SGSC smart meter

In addition for the Retail Trial, the following additional criteria were used:

25. Not part of the Network or Control Group Trials
26. Customer was currently an Energy Australia customer
27. Customer has not requested "do not call"
28. The meters have not been flagged as "Pending turn off"
29. The dwelling is not flagged as a deceased customer
30. The customer does not have an active Ombudsman complaint
31. The customer is not a managed account (i.e. has been flagged as having financial difficulties in paying their bills)
32. The customer is not on the Energy Assist program (i.e. has been flagged as having financial difficulties in paying their bills)
33. The customer has not been flagged as a "Bad credit" customer
34. The dwelling is not flagged as a "temporary supply" site
35. The address of the dwelling as known by Ausgrid matches the address as known by EnergyAustralia

A.3 Geography Discussion

The following section discussing geography is taken from AEFI (2014)

The selection of appropriate geographic locations for the trial was considered critical to producing reliable data that could be accurately extrapolated to assess the viability of a large scale smart grid roll-out in Australia.

The greater Newcastle area was selected as one of the focal points for the trial due to its mix of regional and suburban characteristics that result in representative geography, climate, socioeconomic and demographic factors. The customer demographic and socioeconomic indicators in Newcastle closely reflect the demographic attributes of a typical Australian city. Newcastle's close relationship to the Australian average for customer demographics is widely accepted and has resulted in the city being used as a test market for products and services prior to their rollout across Australia in the past.

The greater Newcastle, Sydney CBD and Central Coast areas provided a sound representation of the geographic, climate, customer demographic and electricity characteristics of a number of regions throughout Australia. It was felt that the trial would produce nationally transferable results. Importantly, the trial locations:

- Included a mix of both urban and regional areas
- Had demographic characteristics closely reflecting the national average in terms of household income, household occupancy, English proficiency, housing types, tenure types, energy sources and appliance stock. In addition, the trial locations contained sufficient variability in these characteristics to test their impact on measured outcomes
- Had similar climates to a large portion of the Australian population including both Climate Zones 5 and 62, in which 60-65 per cent of Australia's population is located
- Demonstrated energy consumption patterns reflective of the Australian population, including both summer and winter peaks in energy demand
- Had sufficient variability in topographic and terrain characteristics to allow accurate testing of alternative technologies
- Demonstrated a range of different overhead and underground network configurations, both radial and meshed networks, and had rural, urban and CBD characteristics typical of Australian networks
- Contained several areas with high network utilisation making them good locations to demonstrate energy efficiency and demand management initiatives.

The climate zones used for the purposes of the Smart Grid, Smart City Project were based on those produced by the Australian Building Codes Board, http://www.abcb.gov.au/en/ma initiatives/energy-efficiency/climate-zone-maps last published in December 2012.

Given the different network types captured by these varying geographic, socioeconomic, demographic and electricity network conditions, it was felt that these areas were broadly representative of a large portion of the Australian population.

Each of the SGSC trial districts and their specific characteristics are discussed below and shown in Figure A.1.

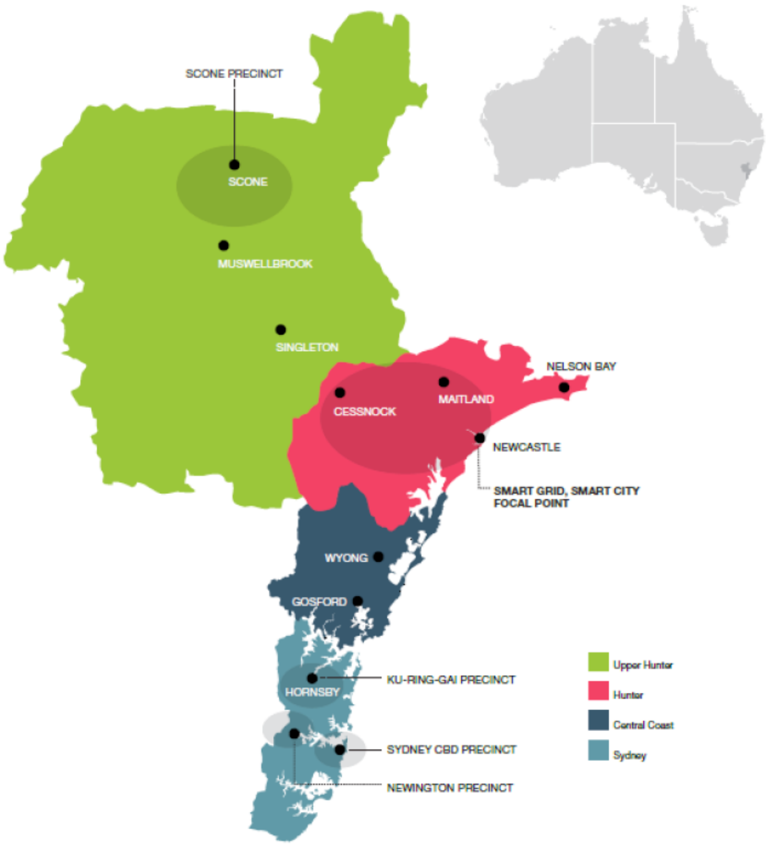

Figure A.1: Map of Trial Locations from Ausgrid (2014)

Greater Newcastle area

The greater Newcastle area was selected as the focal point for the trial, due to its good mix of regional and suburban characteristics, representative geography, climate, socioeconomic and demographic factors of the broader Australian population. The customer demographics and socioeconomic indicators of the area closely reflect the demographics of a typical Australian city.

Sydney CBD

Part of the City of Sydney Local Government Area (LGA), this area provided additional high density residential buildings and large scale co-generation.

Ku-Ring-Gai area

Situated on the north shore of Sydney, this area provided additional testing of high income demographics. The area also provided a high number of customers with swimming pools (approximately 36 per cent in some areas of the Local Government Area) for testing new products.

Newington area

Part of the Auburn LGA, this area provided a typical Western Sydney climate zone and suburban environment for broad testing. The suburb added a high multicultural population and contains the highest penetration of customer photovoltaic energy generation, assisting in the trial of renewable generation and storage applications.

Scone area

Part of the Upper Hunter LGA, this area provided additional rural characteristics and a more extreme climate zone. The area provided a rural network to perform end of feeder trials and much lower levels of internet use representative of more rural geographies.

Nelson Bay area

An area north of Newcastle in NSW, included two zone transformers with eight feeders exhibiting signs of moderate voltage constraint, supporting around 10,000 customers spread across 210 distribution transformers. This area is typical of older (brownfield) distribution zones with existing constraints which made it amenable to testing the potential benefits of grid application technologies.

Appendix B

Additional Data Analysis

B.1 Mean Differences Tables

Table B.1: Mean Differences - Control, IHD, Portal, Portal+IHD, Portal+Plug

	Control	IHD		Portal		IHD+Portal		Portal+Plug	
	Mean	Mean	Difference	Mean	Difference	Mean	Difference	Mean	Difference
Income									
- Low {0,1}	0.405	0.416	0.011	0.244	−0.161∗∗∗	0.253	−0.152∗∗∗	0.231	−0.174∗∗
	[0.491]	[0.493]	[0.022]	[0.430]	[0.016]	[0.436]	[0.038]	[0.425]	[0.062]
- Med {0,1}	0.329	0.318	−0.011	0.274	−0.055∗∗∗	0.371	0.042	0.246	−0.083
	[0.470]	[0.466]	[0.021]	[0.446]	[0.016]	[0.484]	[0.037]	[0.434]	[0.059]
- High {0,1}	0.266	0.266	0.000	0.482	0.216∗∗∗	0.376	0.110∗∗	0.523	0.257∗∗∗
	[0.442]	[0.442]	[0.020]	[0.500]	[0.016]	[0.486]	[0.035]	[0.503]	[0.056]
Gas Usage									
- Low {0,1}	0.361	0.383	0.022	0.306	−0.054∗∗	0.483	0.122∗∗	0.292	−0.069
	[0.48]	[0.486]	[0.021]	[0.461]	[0.017]	[0.501]	[0.038]	[0.458]	[0.06]
- Med {0,1}	0.461	0.356	−0.105∗∗∗	0.365	−0.096∗∗∗	0.320	−0.141∗∗∗	0.508	0.046
	[0.499]	[0.479]	[0.022]	[0.482]	[0.017]	[0.468]	[0.039]	[0.504]	[0.063]
- High {0,1}	0.178	0.261	0.083∗∗∗	0.328	0.150∗∗∗	0.197	0.019	0.200	0.022
	[0.382]	[0.44]	[0.018]	[0.47]	[0.015]	[0.399]	[0.03]	[0.403]	[0.048]
Electicity Usage									
- Low {0,1}	0.492	0.476	−0.016	0.325	−0.167∗∗∗	0.489	−0.003	0.385	−0.107
	[0.5]	[0.5]	[0.022]	[0.468]	[0.017]	[0.501]	[0.039]	[0.490]	[0.063]
- Med {0,1}	0.275	0.309	0.034	0.282	0.006	0.326	0.051	0.323	0.048
	[0.447]	[0.463]	[0.020]	[0.45]	[0.016]	[0.470]	[0.035]	[0.471]	[0.056]
- High {0,1}	0.233	0.215	−0.018	0.394	0.161∗∗∗	0.185	−0.047	0.292	0.060
	[0.423]	[0.411]	[0.019]	[0.489]	[0.016]	[0.39]	[0.033]	[0.458]	[0.053]

Dwelling Type									
- Unit {0,1}	0.300	0.300	0.001	0.112	−0.187***	0.230	−0.069	0.369	0.070
	[0.458]	[0.459]	[0.020]	[0.316]	[0.014]	[0.422]	[0.036]	[0.486]	[0.058]
- Not Unit {0,1}	0.700	0.700	−0.001	0.888	0.187***	0.770	0.069	0.631	−0.070
	[0.458]	[0.459]	[0.02]	[0.316]	[0.014]	[0.422]	[0.036]	[0.486]	[0.058]
Number of HHs	2092	666		1325		178		65	

Notes: The means are reported by treatment group, with standard deviations in brackets below. "Difference" displays the difference in means between each treatment group and the control, with standard errors in brackets below.

***Significant at the 1% level

**Significant at the 5% level

*Significant at the 10% level

Table B.2: Mean Differences - LGA - Control, DPP, DPP+IHD, DPP+Portal

	Control	DPP		DPP+IHD		DPP+Portal	
	Mean	Mean	Difference	Mean	Difference	Mean	Difference
Auburn (0-1)	0.194	0.070	−0.124***	0.014	−0.179***	0.024	−0.170***
	[0.395]	[0.256]	[0.02]	[0.119]	[0.012]	[0.152]	[0.022]
Bankstown (0-1)	0.000	0.012	0.012***	0.027	0.027***	0.062	0.062***
	[0.000]	[0.109]	[0.002]	[0.161]	[0.004]	[0.242]	[0.005]
Burwood (0-1)	0.000	0.000	0.000	0.007	0.007***	0.006	0.006***
	[0.000]	[0.000]	[0.000]	[0.081]	[0.002]	[0.077]	[0.002]
Canada Bay (0-1)	0.000	0.005	0.005**	0.002	0.002*	0.003	0.003*
	[0.000]	[0.069]	[0.002]	[0.044]	[0.001]	[0.054]	[0.001]
Canterbury (0-1)	0.000	0.048	0.048***	0.066	0.066***	0.053	0.053***
	[0.000]	[0.215]	[0.005]	[0.248]	[0.005]	[0.225]	[0.005]
Cessnock (0-1)	0.072	0.041	−0.031*	0.146	0.074***	0.047	−0.025
	[0.259]	[0.199]	[0.013]	[0.353]	[0.011]	[0.213]	[0.015]
Concord (0-1)	0.000	0.000	0.000	0.001	0.001	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.031]	[0.001]	[0.000]	[0.000]
Hornsby (0-1)	0.000	0.007	0.007***	0.051	0.051***	0.000	0.000
	[0.000]	[0.085]	[0.002]	[0.219]	[0.005]	[0.000]	[0.000]
Hurstville (0-1)	0.000	0.012	0.012***	0.008	0.008***	0.015	0.015***
	[0.000]	[0.109]	[0.002]	[0.087]	[0.002]	[0.121]	[0.003]
Kogarah (0-1)	0.000	0.002	0.002*	0.005	0.005**	0.000	0.000
	[0.000]	[0.049]	[0.001]	[0.069]	[0.002]	[0.000]	[0.000]
Ku-Ring-Gai (0-1)	0.100	0.174	0.074***	0.092	−0.008	0.180	0.081***
	[0.3]	[0.379]	[0.017]	[0.289]	[0.011]	[0.385]	[0.018]

Lake Macquarie (0-1)	0.147	0.138	−0.010	0.173	0.025	0.207	0.060**
	[0.354]	[0.345]	[0.019]	[0.378]	[0.014]	[0.406]	[0.021]
Mosman (0-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Muswellbrook (0-1)	0.058	0.000	−0.058***	0.005	−0.054***	0.003	−0.055***
	[0.234]	[0.000]	[0.012]	[0.069]	[0.007]	[0.054]	[0.013]
Newcastle (0-1)	0.274	0.292	0.019	0.258	−0.016	0.308	0.034
	[0.446]	[0.455]	[0.024]	[0.438]	[0.017]	[0.462]	[0.026]
Out-Of-Area (0-1)	0.000	0.002	0.002	0.001	0.000	0.000	0.000
	[0.022]	[0.049]	[0.002]	[0.031]	[0.001]	[0.000]	[0.001]
Randwick (0-1)	0.000	0.094	0.094***	0.033	0.033***	0.027	0.027***
	[0.000]	[0.292]	[0.006]	[0.18]	[0.004]	[0.161]	[0.004]
Rockdale (0-1)	0.000	0.007	0.007***	0.014	0.014***	0.003	0.003*
	[0.000]	[0.085]	[0.002]	[0.119]	[0.003]	[0.054]	[0.001]
Scone (0-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.022]	[0.000]	[0.001]	[0.000]	[0.001]	[0.000]	[0.001]
South Sydney (0-1)	0.134	0.085	−0.049**	0.014	−0.120***	0.012	−0.122***
	[0.341]	[0.279]	[0.018]	[0.119]	[0.011]	[0.108]	[0.019]
Strathfield (0-1)	0.000	0.000	0.000	0.006	0.006***	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.075]	[0.002]	[0.000]	[0.000]
Sydney (0-1)	0.020	0.005	−0.015*	0.002	−0.018***	0.006	−0.014
	[0.14]	[0.069]	[0.007]	[0.044]	[0.004]	[0.077]	[0.008]
Waverley (0-1)	0.000	0.000	0.000	0.047	0.047***	0.003	0.003*
	[0.000]	[0.000]	[0.000]	[0.211]	[0.005]	[0.054]	[0.001]
Woollahra (0-1)	0.000	0.005	0.005**	0.030	0.030***	0.041	0.041***
	[0.000]	[0.069]	[0.002]	[0.17]	[0.004]	[0.2]	[0.004]
Wyong (0-1)	0.000	0.000	0.000	0.001	0.001	0.000	0.000

	[0.000]	[0.000]	[0.000]	[0.031]	[0.001]	[0.000]	[0.000]
Number of Households	2091	414		1048		338	

Notes: The means are reported by treatment group, with standard deviations in brackets below. ”Difference” displays the difference in means between each treatment group and the control, with standard errors in brackets below.

***Significant at the 1% level

**Significant at the 5% level

*Significant at the 10% level

Table B.3: Mean Differences - LGA - Control, DPP+Plug, DPR and DPR+IHD

	Control	DPP+Plug		DPR		DPR+IHD	
	Mean	Mean	Difference	Mean	Difference	Mean	Difference
Auburn (0-1)	0.194	0.007	−0.187∗∗∗	0.142	−0.051∗∗	0.127	−0.066∗∗∗
	[0.395]	[0.084]	[0.033]	[0.35]	[0.017]	[0.334]	[0.017]
Bankstown (0-1)	0.000	0.007	0.007∗∗∗	0.000	0.000	0.000	0.000
	[0.000]	[0.084]	[0.002]	[0.000]	[0.000]	[0.000]	[0.000]
Burwood (0-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Canada Bay (0-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Canterbury (0-1)	0.000	0.028	0.028∗∗∗	0.000	0.000	0.000	0.000
	[0.000]	[0.166]	[0.004]	[0.000]	[0.000]	[0.000]	[0.000]
Cessnock (0-1)	0.072	0.028	−0.044∗	0.031	−0.041∗∗∗	0.029	−0.043∗∗∗
	[0.259]	[0.166]	[0.022]	[0.173]	[0.011]	[0.167]	[0.011]
Concord (0-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Hornsby (0-1)	0.000	0.014	0.014∗∗∗	0.000	0.000	0.000	0.000
	[0.000]	[0.118]	[0.003]	[0.000]	[0.000]	[0.000]	[0.000]
Hurstville (0-1)	0.000	0.014	0.014∗∗∗	0.000	0.000	0.000	0.000
	[0.000]	[0.118]	[0.003]	[0.000]	[0.000]	[0.000]	[0.000]
Kogarah (0-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Ku-Ring-Gai (0-1)	0.100	0.254	0.154∗∗∗	0.194	0.094∗∗∗	0.209	0.109∗∗∗
	[0.3]	[0.437]	[0.027]	[0.396]	[0.014]	[0.407]	[0.015]

Lake Macquarie (0-1)	0.147 [0.354]	0.176 [0.382]	0.029 [0.031]	0.191 [0.393]	0.044∗∗ [0.016]	0.227 [0.419]	0.080∗∗∗ [0.017]
Mosman (0-1)	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]
Muswellbrook (0-1)	0.058 [0.234]	0.000 [0.000]	−0.058∗∗ [0.02]	0.048 [0.215]	−0.010 [0.01]	0.062 [0.242]	0.004 [0.011]
Newcastle (0-1)	0.274 [0.446]	0.317 [0.467]	0.043 [0.039]	0.235 [0.424]	−0.039∗ [0.019]	0.198 [0.399]	−0.075∗∗∗ [0.019]
Out-Of-Area (0-1)	0.000 [0.022]	0.007 [0.084]	0.007∗ [0.003]	0.000 [0.000]	0.000 [0.001]	0.000 [0.000]	0.000 [0.001]
Randwick (0-1)	0.000 [0.000]	0.120 [0.326]	0.120∗∗∗ [0.007]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]
Rockdale (0-1)	0.000 [0.000]	0.014 [0.118]	0.014∗∗∗ [0.003]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]
Scone (0-1)	0.000 [0.022]	0.000 [0.000]	0.000 [0.002]	0.026 [0.161]	0.026∗∗∗ [0.004]	0.017 [0.128]	0.016∗∗∗ [0.003]
South Sydney (0-1)	0.134 [0.341]	0.014 [0.118]	−0.120∗∗∗ [0.029]	0.098 [0.298]	−0.036∗ [0.015]	0.088 [0.283]	−0.046∗∗ [0.015]
Strathfield (0-1)	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]
Sydney (0-1)	0.020 [0.14]	0.000 [0.000]	−0.020 [0.012]	0.034 [0.181]	0.014∗ [0.007]	0.042 [0.202]	0.022∗∗ [0.007]
Waverley (0-1)	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]
Woollahra (0-1)	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]
Wyong (0-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000

	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Number of HHs	2092	142		681		660	

Notes: The means are reported by treatment group, with standard deviations in brackets below. "Difference" displays the difference in means between each treatment group and the control, with standard errors in brackets below.

***Significant at the 1% level

**Significant at the 5% level

*Significant at the 10% level

Table B.4: Mean Differences - LGA - Control, DPP, DPP+IHD, DPP+Portal

	Control	IHD		Portal		IHD+Portal		Portal+Plug	
	Mean	Mean	Difference	Mean	Difference	Mean	Difference	Mean	Difference
Auburn (0-1)	0.194	0.119	−0.075∗∗∗	0.102	−0.092∗∗∗	0.051	−0.143∗∗∗	0.062	−0.132∗∗
	[0.395]	[0.324]	[0.017]	[0.303]	[0.013]	[0.22]	[0.03]	[0.242]	[0.049]
Bankstown (0-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Burwood (0-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Canada Bay (0-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Canterbury (0-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Cessnock (0-1)	0.072	0.057	−0.015	0.058	−0.014	0.023	−0.050∗	0.108	0.035
	[0.259]	[0.232]	[0.011]	[0.234]	[0.009]	[0.149]	[0.02]	[0.312]	[0.033]
Concord (0-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Hornsby (0-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Hurstville (0-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Kogarah (0-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Ku-Ring-Gai (0-1)	0.100	0.164	0.064∗∗∗	0.304	0.204∗∗∗	0.147	0.047∗	0.200	0.100∗∗
	[0.3]	[0.37]	[0.014]	[0.46]	[0.013]	[0.355]	[0.024]	[0.403]	[0.038]

Lake Macquarie (0-1)	0.147	0.273	0.126***	0.167	0.020	0.220	0.073**	0.169	0.022
	[0.354]	[0.446]	[0.017]	[0.373]	[0.013]	[0.416]	[0.028]	[0.378]	[0.045]
Mosman (0-1)	0.000	0.002	0.002	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.039]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Muswellbrook (0-1)	0.058	0.069	0.011	0.026	−0.032***	0.141	0.083***	0.015	−0.043
	[0.234]	[0.254]	[0.011]	[0.16]	[0.007]	[0.349]	[0.019]	[0.124]	[0.029]
Newcastle (0-1)	0.274	0.195	−0.078***	0.221	−0.052***	0.249	−0.025	0.231	−0.043
	[0.446]	[0.397]	[0.019]	[0.415]	[0.015]	[0.433]	[0.035]	[0.425]	[0.056]
Out-Of-Area (0-1)	0.000	0.000	0.000	0.002	0.001	0.000	0.000	0.000	0.000
	[0.022]	[0.000]	[0.001]	[0.039]	[0.001]	[0.000]	[0.002]	[0.000]	[0.003]
Randwick (0-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Rockdale (0-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Scone (0-1)	0.000	0.051	0.051***	0.045	0.044***	0.045	0.045***	0.031	0.030***
	[0.022]	[0.22]	[0.005]	[0.206]	[0.005]	[0.208]	[0.005]	[0.174]	[0.005]
South Sydney (0-1)	0.134	0.026	−0.108***	0.063	−0.071***	0.096	−0.038	0.169	0.035
	[0.341]	[0.158]	[0.014]	[0.242]	[0.011]	[0.295]	[0.026]	[0.378]	[0.043]
Strathfield (0-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Sydney (0-1)	0.020	0.045	0.025***	0.012	−0.008	0.028	0.008	0.015	−0.005
	[0.14]	[0.208]	[0.007]	[0.109]	[0.005]	[0.166]	[0.011]	[0.124]	[0.018]
Waverley (0-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Woollahra (0-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Wyong (0-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Number of HHs	2091	666	1324	17	65

Notes: The means are reported by treatment group, with standard deviations in brackets below. "Difference" displays the difference in means between each treatment group and the control, with standard errors in brackets below.

***Significant at the 1% level

**Significant at the 5% level

*Significant at the 10% level

B.2 Results - Full Output

Table B.5: Peak Event Models - Full Output

Main Models	(1)	(2)	(3)	(4)	(5)
$\text{Group}_{DPP-only}$*Event_{DPP}	-0.270***	-0.303***	-0.273***	-0.299***	-0.292***
	(0.038)	(0.038)	(0.038)	(0.037)	(0.039)
$\text{Group}_{DPP-only}$*Event_{DPR}	0.075***	0.027	0.046*	0.004	0.020
	(0.019)	(0.019)	(0.018)	(0.018)	(0.019)
$\text{Group}_{DPP+Portal}$*$\text{Event}_{DPP}$	-0.267***	-0.303***	-0.261***	-0.289***	-0.321***
	(0.045)	(0.045)	(0.044)	(0.044)	(0.045)
$\text{Group}_{DPP+Portal}$*$\text{Event}_{DPR}$	0.116***	0.055*	0.089***	0.033	0.030
	(0.022)	(0.022)	(0.021)	(0.021)	(0.021)
$\text{Group}_{DPP+Portal+Plug}$*$\text{Event}_{DPP}$	-0.283***	-0.323***	-0.275***	-0.308***	-0.290***
	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)
$\text{Group}_{DPP+Portal+Plug}$*$\text{Event}_{DPR}$	0.061	-0.013	0.036	-0.033	-0.018
	(0.035)	(0.034)	(0.033)	(0.032)	(0.032)
$\text{Group}_{DPP+IHD}$*Event_{DPP}	-0.225***	-0.267***	-0.232***	-0.267***	-0.337***
	(0.026)	(0.026)	(0.025)	(0.026)	(0.029)
$\text{Group}_{DPP+IHD}$*Event_{DPR}	0.145***	0.054***	0.119***	0.033*	0.007
	(0.015)	(0.015)	(0.015)	(0.014)	(0.016)
$\text{Group}_{DPR-only}$*Event_{DPP}	-0.031	-0.032	-0.032	-0.032	-0.014
	(0.023)	(0.023)	(0.022)	(0.022)	(0.022)
$\text{Group}_{DPR-only}$*Event_{DPR}	-0.112***	-0.112***	-0.121***	-0.121***	-0.113***
	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)
$\text{Group}_{DPR+IHD}$*Event_{DPP}	-0.026	-0.028	-0.027	-0.027	-0.007
	(0.025)	(0.025)	(0.024)	(0.024)	(0.023)
$\text{Group}_{DPR+IHD}$*Event_{DPR}	-0.077***	-0.080***	-0.086***	-0.087***	-0.078***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Group_{Portal}*Event_{DPP}	-0.003	-0.005	-0.006	-0.007	0.023
	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)
Group_{Portal}*Event_{DPR}	0.019	0.019	0.012	0.012	0.019
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
$\text{Group}_{Portal+IHD}$*$\text{Event}_{DPP}$	0.088	0.085	0.081	0.080	0.064
	(0.048)	(0.048)	(0.048)	(0.047)	(0.045)
$\text{Group}_{Portal+IHD}$*$\text{Event}_{DPR}$	0.081**	0.079**	0.074**	0.073**	0.062*
	(0.029)	(0.029)	(0.028)	(0.028)	(0.026)
$\text{Group}_{Portal+Plug}$*$\text{Event}_{DPP}$	0.044	0.041	0.029	0.028	0.048
	(0.073)	(0.073)	(0.071)	(0.071)	(0.066)
$\text{Group}_{Portal+Plug}$*$\text{Event}_{DPR}$	0.094	0.095	0.093	0.095	0.101
	(0.059)	(0.059)	(0.059)	(0.059)	(0.057)

Group_{IHD}*Event_{DPP}	0.000	-0.002	-0.004	-0.005	-0.019
	(0.024)	(0.024)	(0.023)	(0.023)	(0.022)
Group_{IHD}*Event_{DPR}	0.060***	0.058***	0.050**	0.050**	0.036*
	(0.016)	(0.016)	(0.015)	(0.015)	(0.015)
$\text{Group}_{DPP-only}$	0.289***	0.317***			
	(0.040)	(0.040)			
$\text{Group}_{DPP+Portal}$	0.328***	0.357***			
	(0.040)	(0.041)			
$\text{Group}_{DPP+Portal+Plug}$	0.518***	0.547***			
	(0.063)	(0.063)			
$\text{Group}_{DPP+IHD}$	0.212***	0.240***			
	(0.029)	(0.029)			
$\text{Group}_{DPR-only}$	0.186***	0.187***			
	(0.031)	(0.031)			
$\text{Group}_{DPR+IHD}$	0.198***	0.201***			
	(0.032)	(0.032)			
Group_{Portal}	0.404***	0.405***			
	(0.025)	(0.025)			
$\text{Group}_{Portal+IHD}$	0.203***	0.205***			
	(0.045)	(0.045)			
$\text{Group}_{Portal+Plug}$	0.336***	0.335***			
	(0.081)	(0.081)			
Group_{IHD}	0.111***	0.113***			
	(0.033)	(0.033)			
Event_{DPP}	0.186***		0.193***		
	(0.012)		(0.011)		
Event_{DPR}	0.259***		0.271***		
	(0.008)		(0.008)		
Constant	-2.014***				
	(0.017)				
Time FE	No	Yes	No	Yes	Yes
Household FE	No	No	Yes	Yes	Yes
Adjusted R^2	0.016	0.090	0.357	0.431	0.438
Number of Obs. (mill)	195	195	195	195	195

Notes: The dependent variable is $ln(kWh)$ in 30-minute intervals. All specifications include a treatment group indicator, interaction between treatment group and a DPP event, interaction between treatment group and a DPR event and two event window indicators (except where subsumed by time or household fixed effects). Standard errors in brackets are clustered at the household level.

***Significant at the 1% level

**Significant at the 5% level

*Significant at the 10% level

Table B.6: Load Shifting Model - Full Output

	b/se
treatment_event_DPP_1	-0.292***
	(0.039)
treatment_event_DPR_1	0.020
	(0.019)
treatment_event_DPP_2	-0.321***
	(0.045)
treatment_event_DPR_2	0.030
	(0.021)
treatment_event_DPP_3	-0.290***
	(0.061)
treatment_event_DPR_3	-0.018
	(0.032)
treatment_event_DPP_4	-0.336***
	(0.029)
treatment_event_DPR_4	0.008
	(0.016)
treatment_event_DPP_5	-0.014
	(0.022)
treatment_event_DPR_5	-0.113***
	(0.016)
treatment_event_DPP_6	-0.008
	(0.023)
treatment_event_DPR_6	-0.079***
	(0.017)
treatment_event_DPP_7	0.023
	(0.018)
treatment_event_DPR_7	0.019
	(0.013)
treatment_event_DPP_8	0.064
	(0.045)
treatment_event_DPR_8	0.062*
	(0.026)
treatment_event_DPP_9	0.048
	(0.066)
treatment_event_DPR_9	0.101
	(0.057)

treatment_event_DPP_10	-0.019
	(0.022)
treatment_event_DPR_10	0.036*
	(0.015)
2hrs Pre-Event*Group$_{DPP-only}$	-0.003
	(0.010)
2hrs Pre-Event*Group$_{DPP+Portal}$	0.028*
	(0.014)
2hrs Pre-Event*Group$_{DPP+Portal+Plug}$	0.008
	(0.017)
2hrs Pre-Event*Group$_{DPP+IHD}$	0.046***
	(0.009)
2hrs Pre-Event*Group$_{DPR-only}$	-0.017**
	(0.006)
2hrs Pre-Event*Group$_{DPR+IHD}$	-0.012
	(0.007)
2hrs Post-Event*Group$_{DPP-only}$	-0.002
	(0.010)
2hrs Post-Event*Group$_{DPP+Portal}$	0.032*
	(0.014)
2hrs Post-Event*Group$_{DPP+Portal+Plug}$	0.013
	(0.014)
2hrs Post-Event*Group$_{DPP+IHD}$	0.049***
	(0.009)
2hrs Post-Event*Group$_{DPR-only}$	-0.016**
	(0.006)
2hrs Post-Event*Group$_{DPR+IHD}$	-0.011
	(0.007)
Adjusted R^2	0.440
Number of Obs.	195

Notes: The dependent variable is $ln(kWh)$ in 30-minute intervals. All specifications include a treatment group indicator, interaction between treatment group and a DPP event, interaction between treatment group and a DPR event and two event window indicators (except where subsumed by time or household fixed effects). Standard errors in brackets are clustered at the household level.

***Significant at the 1% level

**Significant at the 5% level

*Significant at the 10% level

Table B.7: Placebo Test - Full Output

Main Models	(1)	(2)	(3)	(4)	(5)
	b/se	b/se	b/se	b/se	b/se
Group$_{DPP-only}$*Event$_{DPP}$	-0.001	-0.007	-0.003	-0.002	-0.008
	(0.017)	(0.014)	(0.015)	(0.013)	(0.013)
Group$_{DPP+Portal}$*Event$_{DPP}$	0.017	0.015	0.024	0.028	0.020
	(0.021)	(0.019)	(0.020)	(0.018)	(0.017)
Group$_{DPP+Portal+Plug}$*Event$_{DPP}$	0.007	0.007	0.015	0.022	0.019
	(0.022)	(0.020)	(0.020)	(0.019)	(0.018)
Group$_{DPP+IHD}$*Event$_{DPP}$	0.042**	0.043***	0.037**	0.044***	0.032***
	(0.013)	(0.010)	(0.012)	(0.009)	(0.008)
Group$_{DPR}$*Event$_{DPP}$	-0.030*	-0.019	-0.030*	-0.019	-0.016
	(0.015)	(0.012)	(0.014)	(0.011)	(0.011)
Group$_{DPR+IHD}$*Event$_{DPP}$	-0.026	-0.016	-0.025	-0.015	-0.011
	(0.016)	(0.013)	(0.015)	(0.013)	(0.013)
Group$_{Portal}$*Event$_{DPP}$	-0.032*	-0.021*	-0.034**	-0.023**	-0.013
	(0.012)	(0.009)	(0.012)	(0.008)	(0.008)
Group$_{Portal+IHD}$*Event$_{DPP}$	-0.025	-0.008	-0.027	-0.010	-0.012
	(0.030)	(0.029)	(0.029)	(0.028)	(0.028)
Group$_{Portal+Plug}$*Event$_{DPP}$	-0.015	-0.002	-0.026	-0.013	-0.009
	(0.036)	(0.035)	(0.032)	(0.031)	(0.030)
Group$_{IHD}$*Event$_{DPP}$	-0.029	-0.020	-0.033*	-0.022	-0.020
	(0.016)	(0.013)	(0.015)	(0.012)	(0.012)
Group$_{DPP-only}$*Event$_{DPR}$	0.025*	0.010	-0.005	-0.006	-0.009
	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)
Group$_{DPP+Portal}$*Event$_{DPR}$	0.037**	0.020	0.008	0.004	-0.002
	(0.012)	(0.011)	(0.010)	(0.009)	(0.009)
Group$_{DPP+Portal+Plug}$*Event$_{DPR}$	-0.003	-0.023	-0.027	-0.034*	-0.029
	(0.021)	(0.021)	(0.016)	(0.015)	(0.015)
Group$_{DPP+IHD}$*Event$_{DPR}$	0.042***	0.022**	0.016*	0.008	-0.003
	(0.009)	(0.007)	(0.008)	(0.006)	(0.006)
Group$_{DPR-only}$*Event$_{DPR}$	-0.004	0.000	-0.013	-0.002	-0.001
	(0.008)	(0.007)	(0.008)	(0.006)	(0.006)
Group$_{DPR+IHD}$*Event$_{DPR}$	-0.003	-0.003	-0.012	-0.004	-0.003
	(0.009)	(0.007)	(0.008)	(0.007)	(0.007)
Group$_{Portal}$*Event$_{DPR}$	-0.003	-0.001	-0.010	-0.001	0.000
	(0.007)	(0.005)	(0.006)	(0.004)	(0.004)
Group$_{Portal+IHD}$*Event$_{DPR}$	0.015	0.013	0.009	0.015	0.017
	(0.015)	(0.015)	(0.014)	(0.013)	(0.013)
Group$_{Portal+Plug}$*Event$_{DPR}$	-0.049*	-0.038	-0.048**	-0.030	-0.025
	(0.021)	(0.021)	(0.019)	(0.018)	(0.018)

$\text{Group}_{IHD}{*}\text{Event}_{DPR}$	-0.001	0.001	-0.011	-0.001	0.000
	(0.008)	(0.007)	(0.008)	(0.006)	(0.006)
Group_{DPP}	0.289***	0.316***			
	(0.040)	(0.040)			
$\text{Group}_{DPP+Portal}$	0.328***	0.356***			
	(0.040)	(0.041)			
$\text{Group}_{DPP+Plug}$	0.518***	0.547***			
	(0.063)	(0.063)			
$\text{Group}_{DPP+IHD}$	0.212***	0.239***			
	(0.029)	(0.029)			
Group_{DPR}	0.186***	0.186***			
	(0.031)	(0.031)			
$\text{Group}_{DPR+IHD}$	0.198***	0.201***			
	(0.032)	(0.032)			
Group_{Portal}	0.404***	0.405***			
	(0.025)	(0.025)			
$\text{Group}_{Portal+IHD}$	0.204***	0.205***			
	(0.045)	(0.045)			
$\text{Group}_{Portal+Plug}$	0.336***	0.336***			
	(0.081)	(0.081)			
Group_{IHD}	0.111***	0.113***			
	(0.033)	(0.033)			
Event_{DPP}	-0.052***		-0.046***		
	(0.008)		(0.007)		
Event_{DPR}	-0.025***		-0.013**		
	(0.005)		(0.004)		
Constant	-2.013***				
	(0.017)				
Time FE	No	Yes	No	Yes	Yes
Household FE	No	No	Yes	Yes	Yes
Adjusted R^2	0.015	0.090	0.357	0.431	0.438
Number of Obs. (mill)	195	195	195	195	195

Notes: The dependent variable is $ln(kWh)$ in 30-minute intervals. All specifications include a treatment group indicator, interaction between treatment group and a DPP event, interaction between treatment group and a DPR event and two event window indicators (except where subsumed by time or household fixed effects). Standard errors in brackets are clustered at the household level.

***Significant at the 1% level

**Significant at the 5% level

*Significant at the 10% level

B.3 Graphs of Habit Formation - Full Output

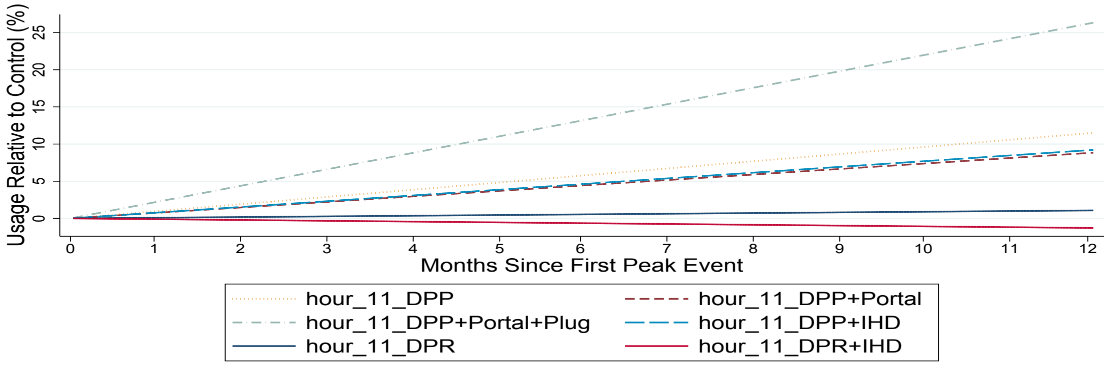

Figure B.1: Linear Trend for Hour 1100

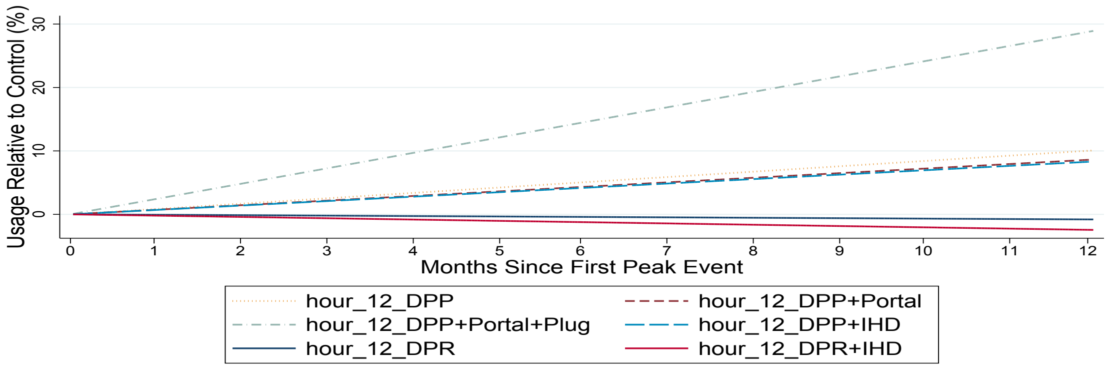

Figure B.2: Linear Trend for Hour 1200

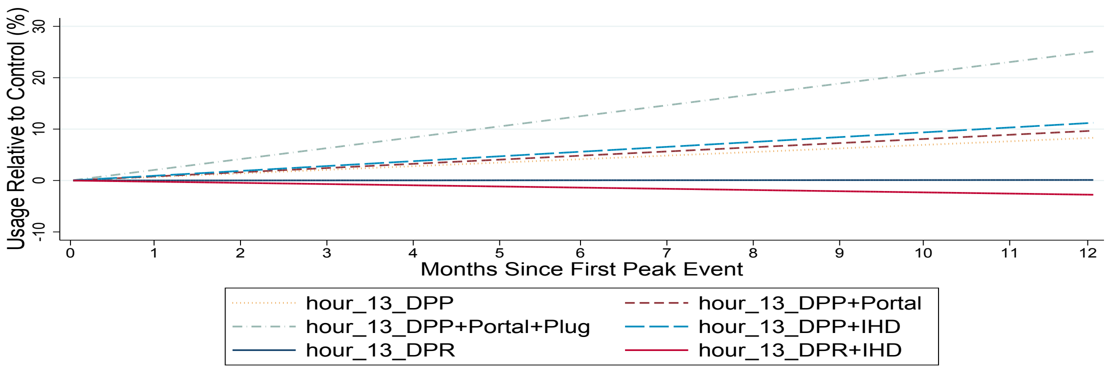

Figure B.3: Linear Trend for Hour 1300

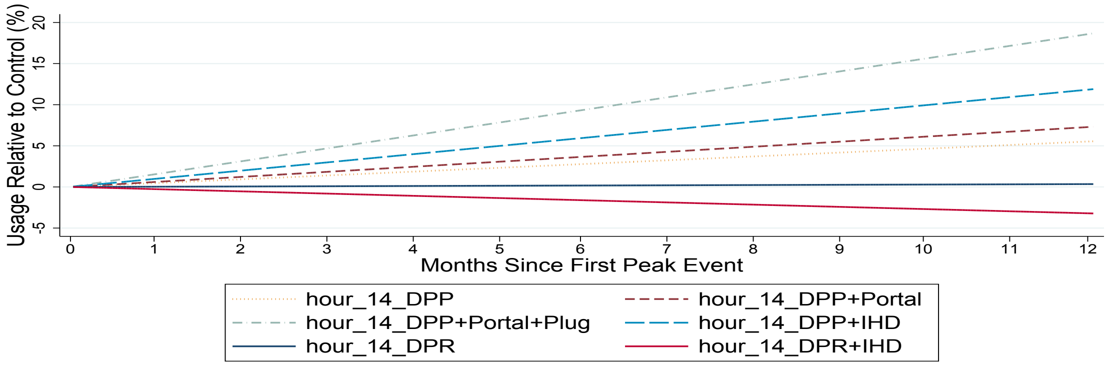

Figure B.4: Linear Trend for Hour 1400

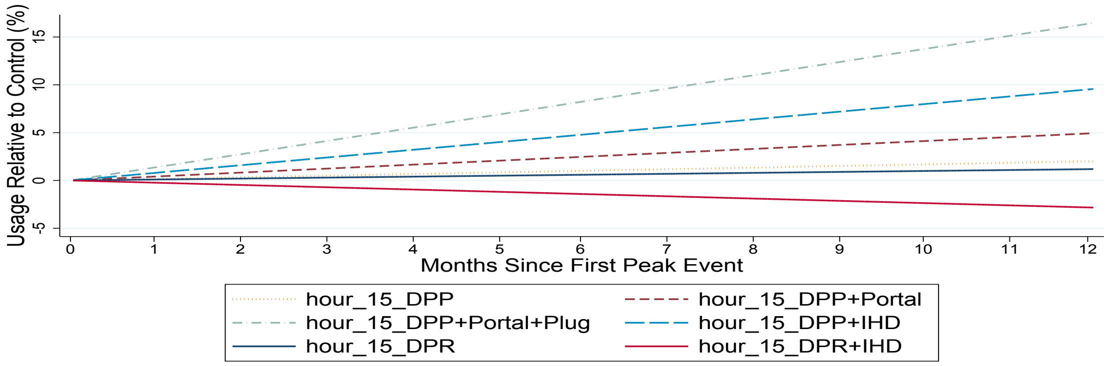

Figure B.5: Linear Trend for Hour 1500

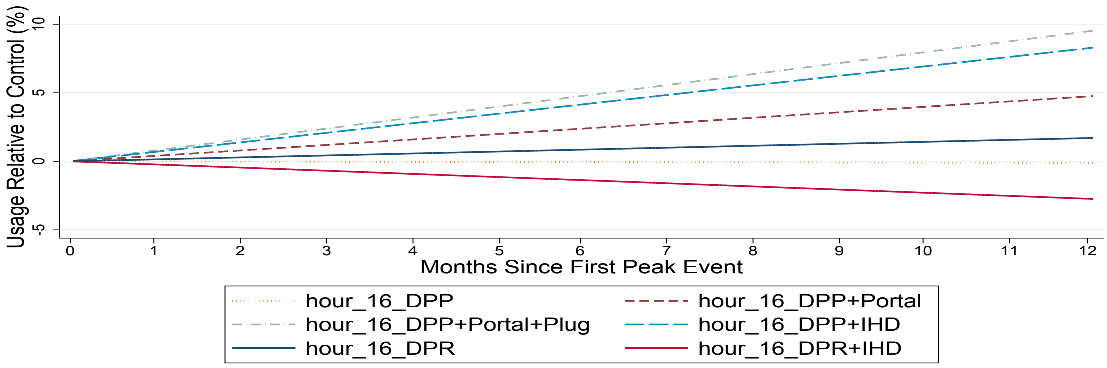

Figure B.6: Linear Trend for Hour 1600

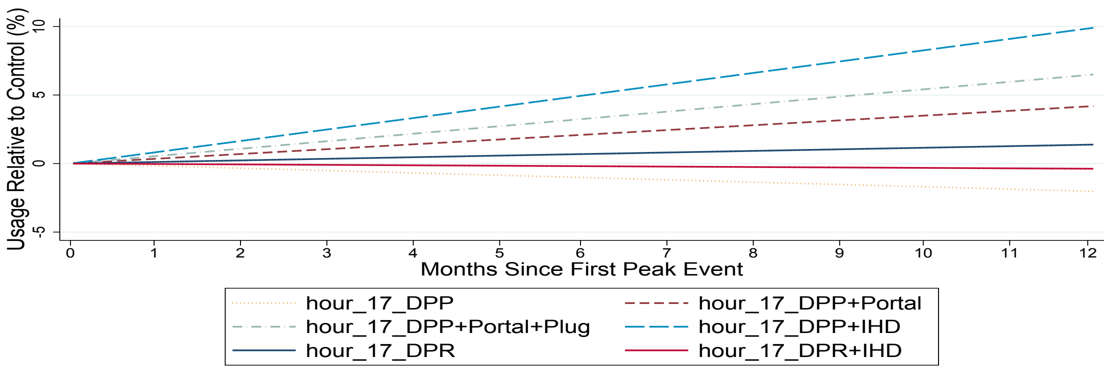

Figure B.7: Linear Trend for Hour 1700

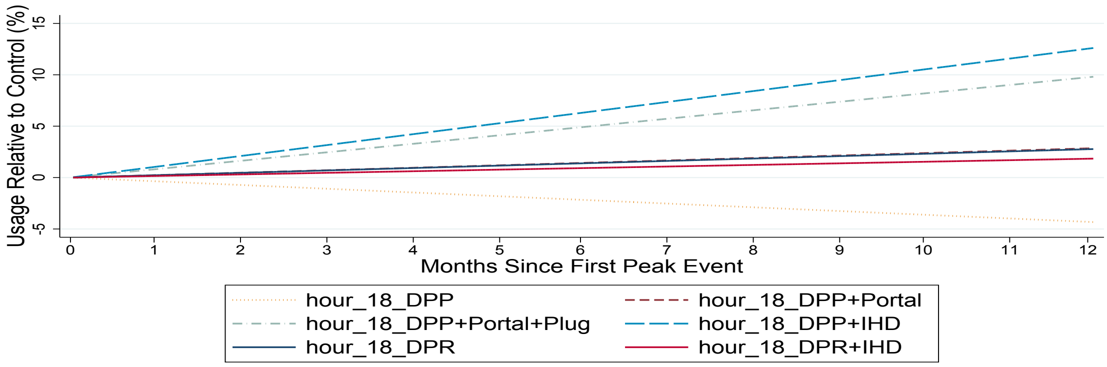

Figure B.8: Linear Trend for Hour 1800

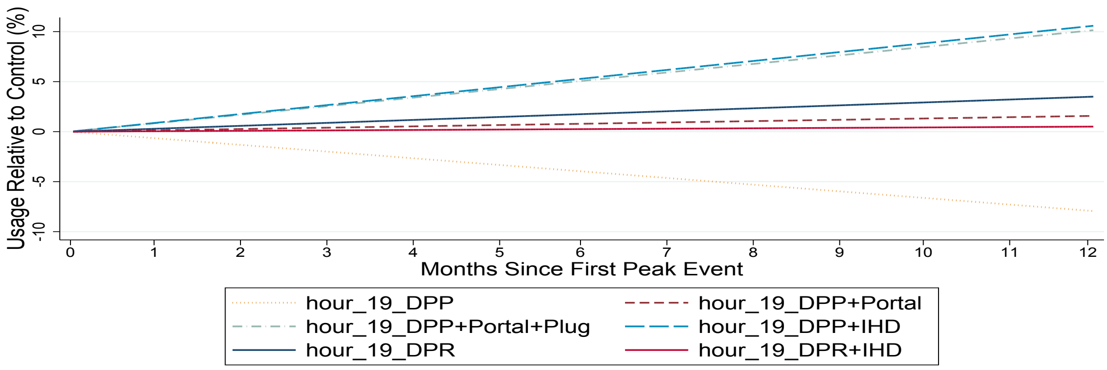

Figure B.9: Linear Trend for Hour 1900

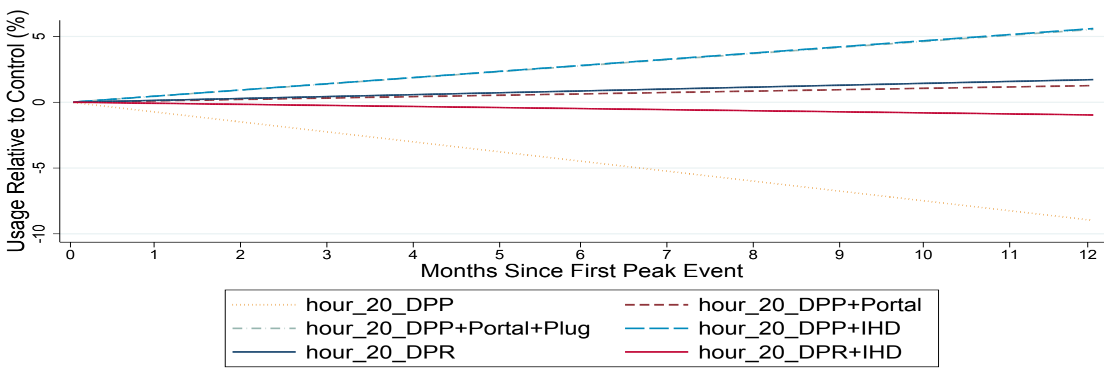

Figure B.10: Linear Trend for Hour 2000

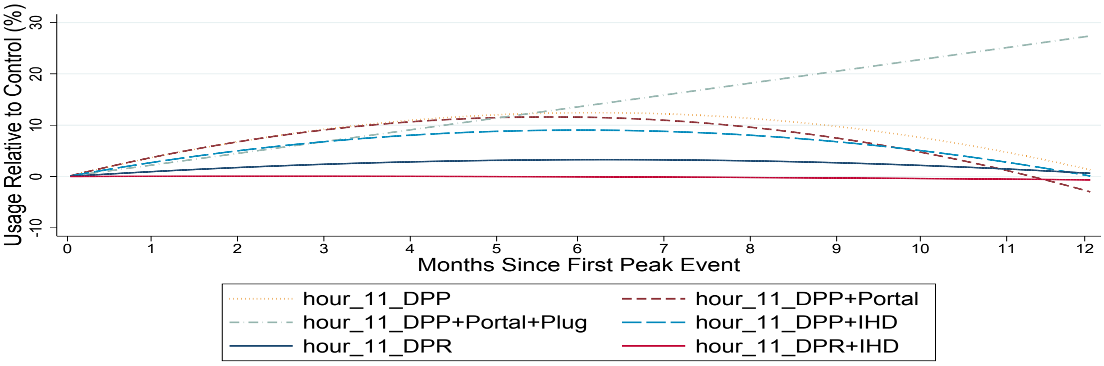

Figure B.11: Quadratic Trend for Hour 1100

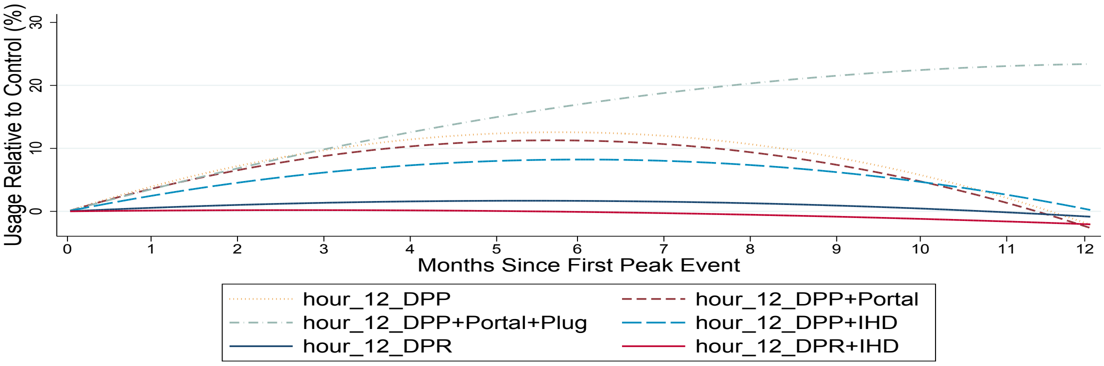

Figure B.12: Quadratic Trend for Hour 1200

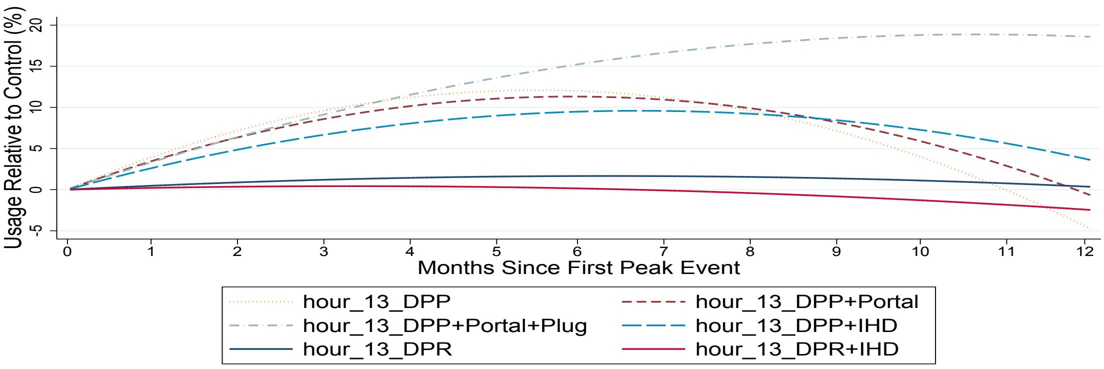

Figure B.13: Quadratic Trend for Hour 1300

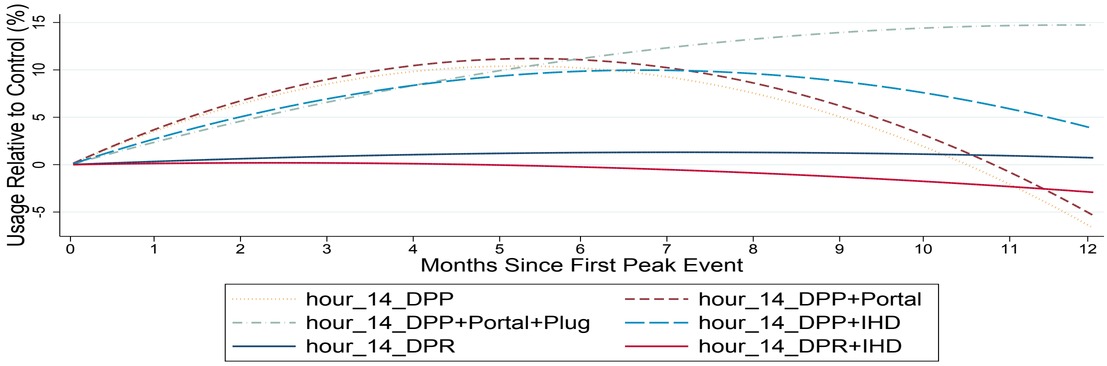

Figure B.14: Quadratic Trend for Hour 1400

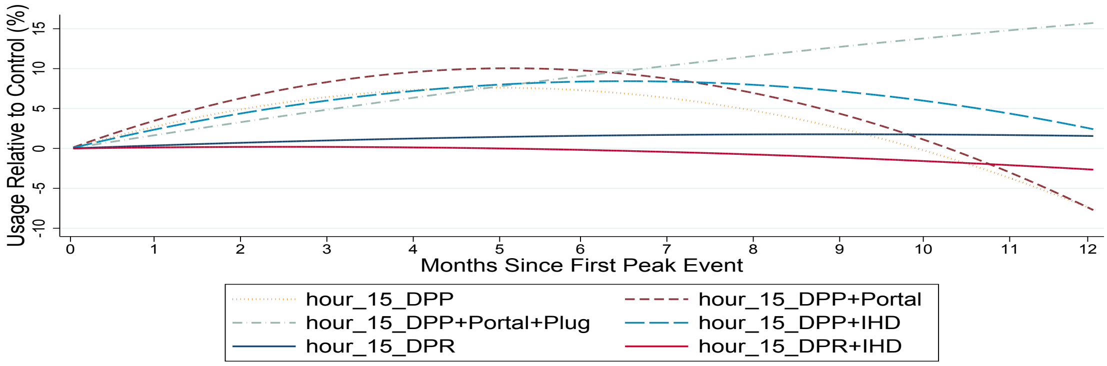

Figure B.15: Quadratic Trend for Hour 1500

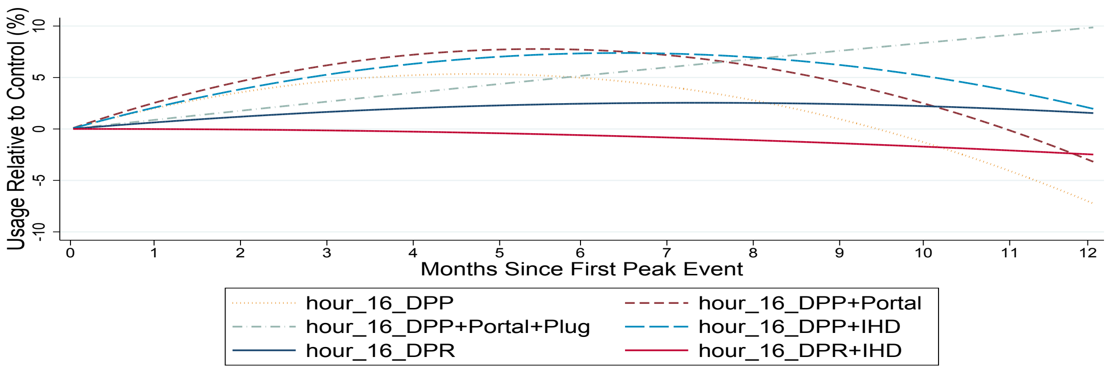

Figure B.16: Quadratic Trend for Hour 1600

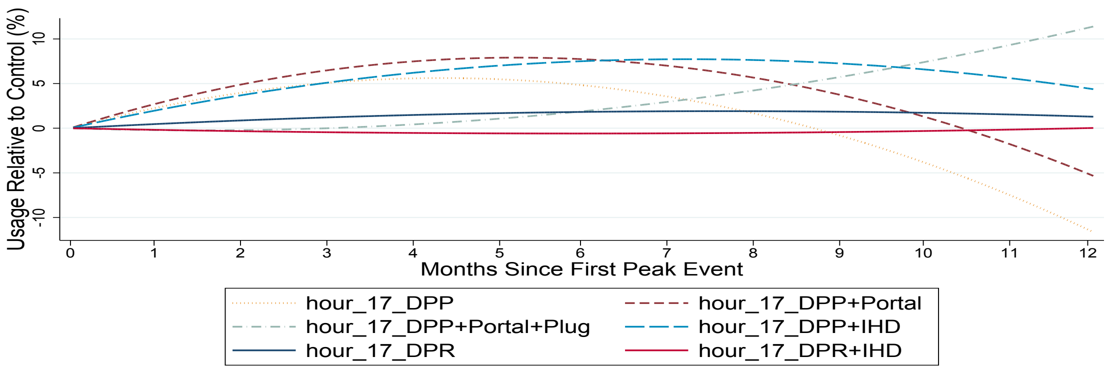

Figure B.17: Quadratic Trend for Hour 1700

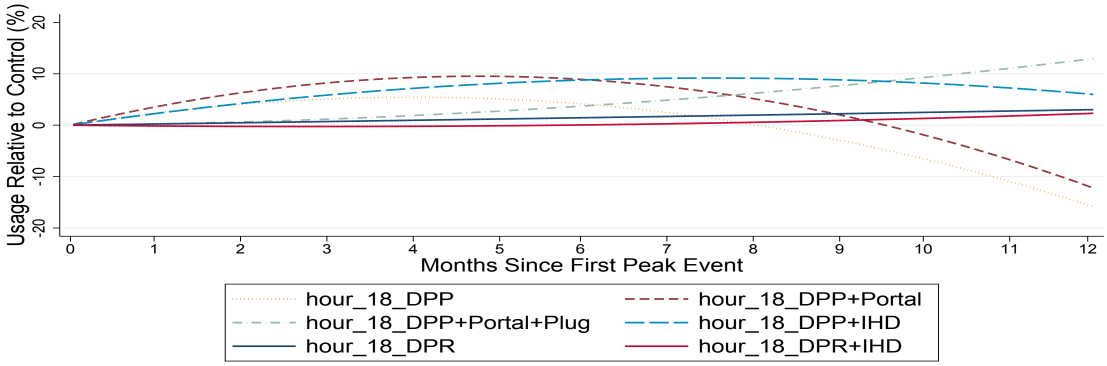

Figure B.18: Quadratic Trend for Hour 1800

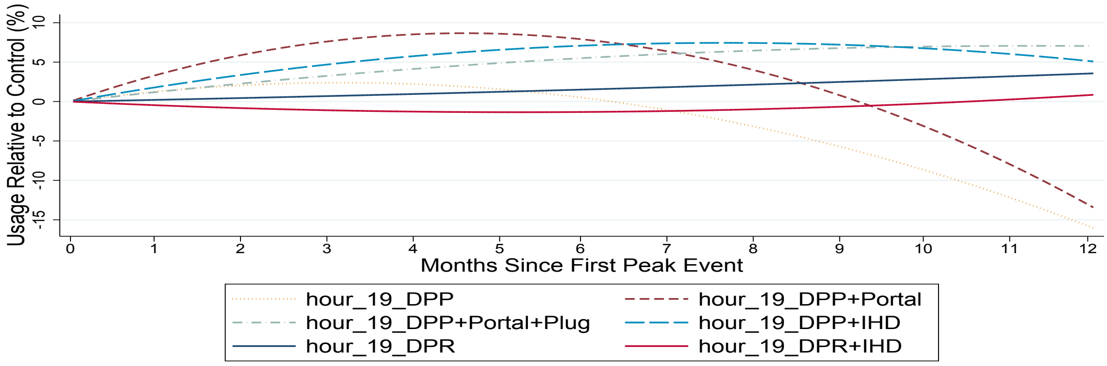

Figure B.19: Quadratic Trend for Hour 1900

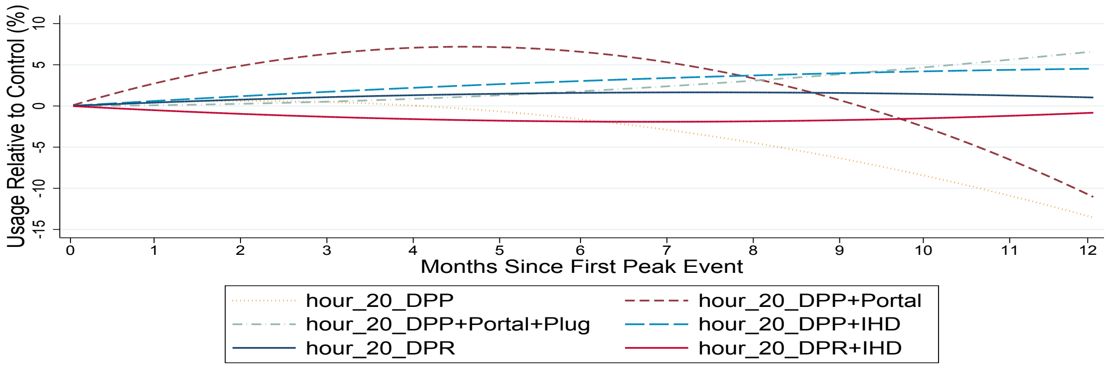

Figure B.20: Quadratic Trend for Hour 2000

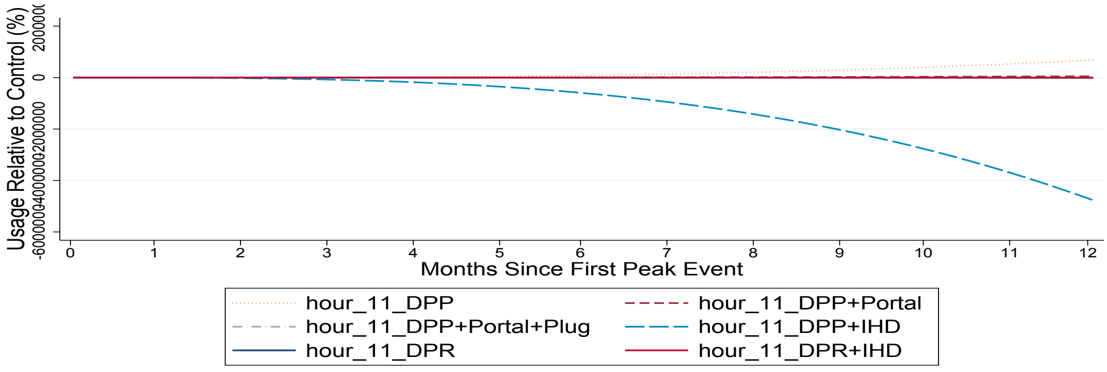

Figure B.21: Cubic Trend for Hour 1100

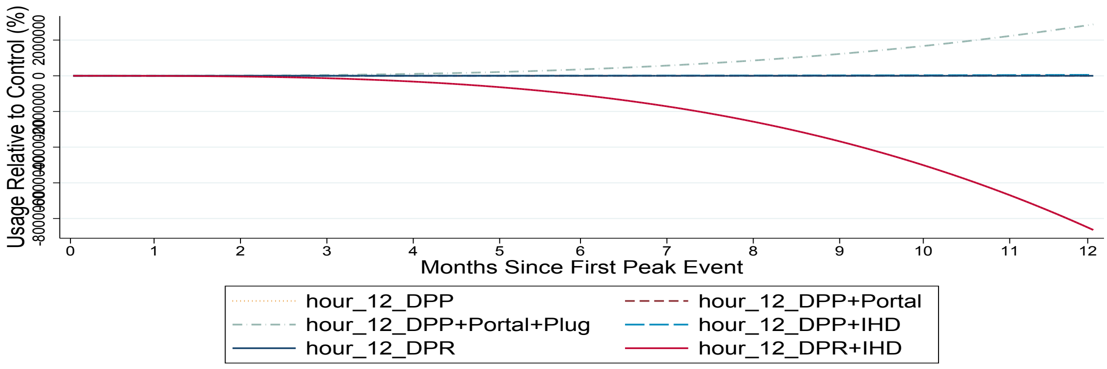

Figure B.22: Cubic Trend for Hour 1200

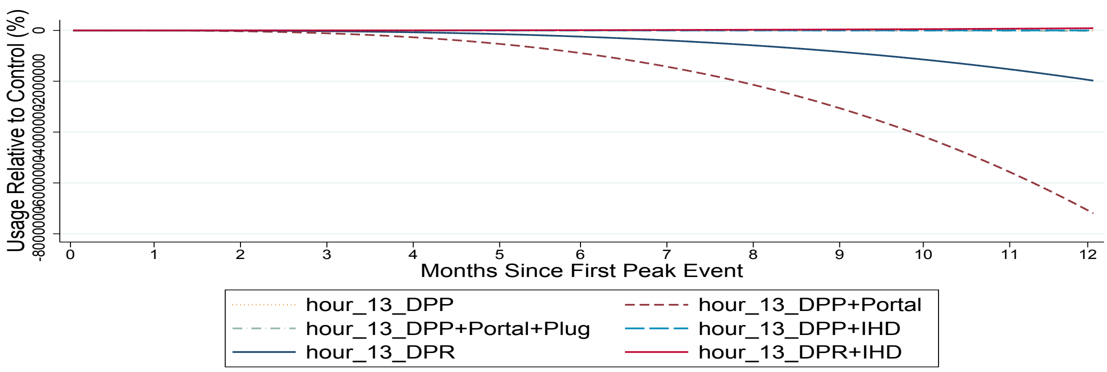

Figure B.23: Cubic Trend for Hour 1300

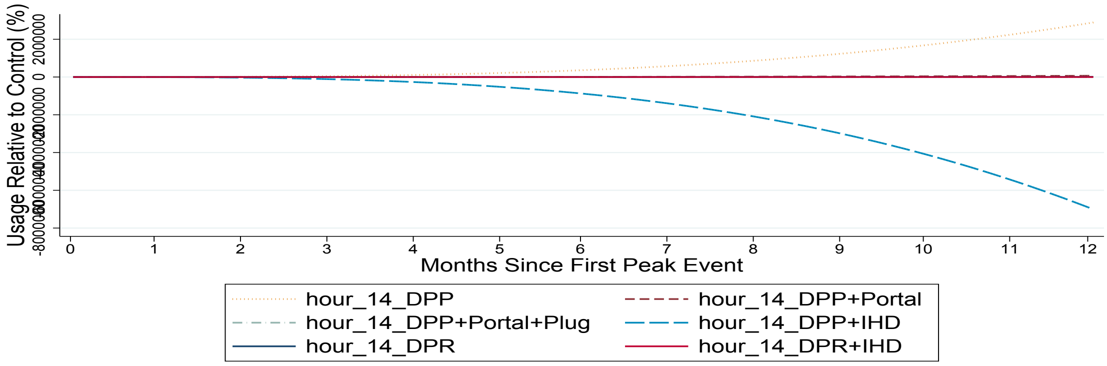

Figure B.24: Cubic Trend for Hour 1400

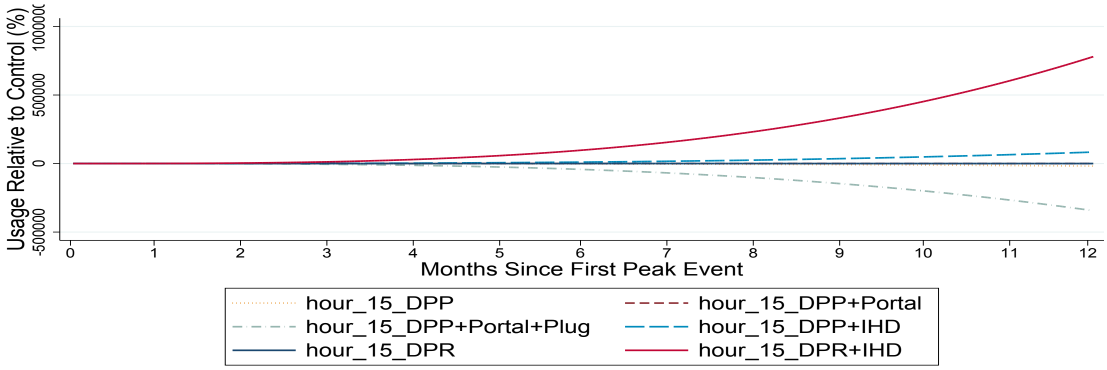

Figure B.25: Cubic Trend for Hour 1500

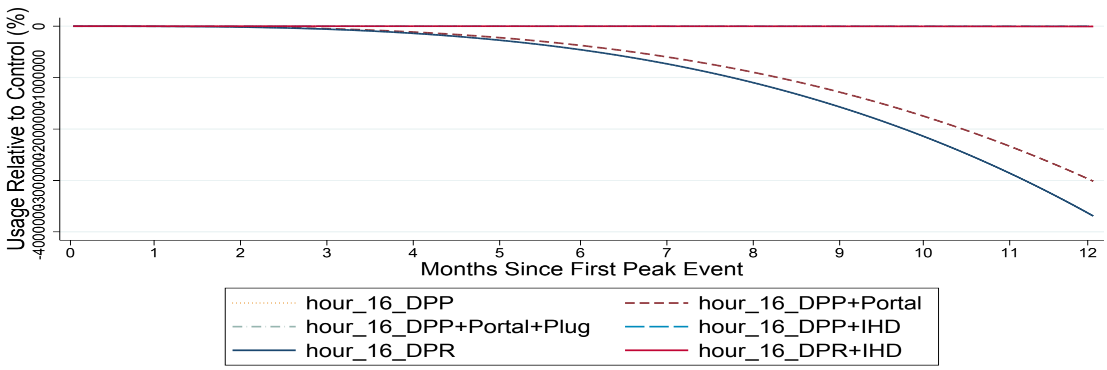

Figure B.26: Cubic Trend for Hour 1600

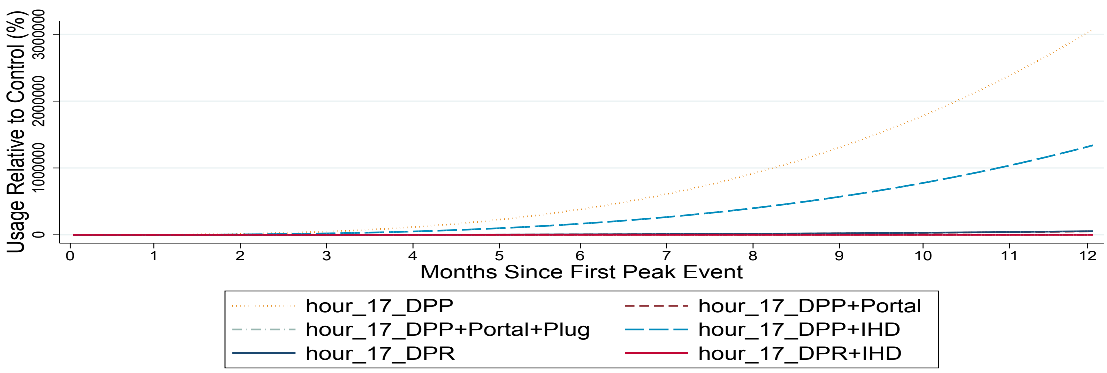

Figure B.27: Cubic Trend for Hour 1700

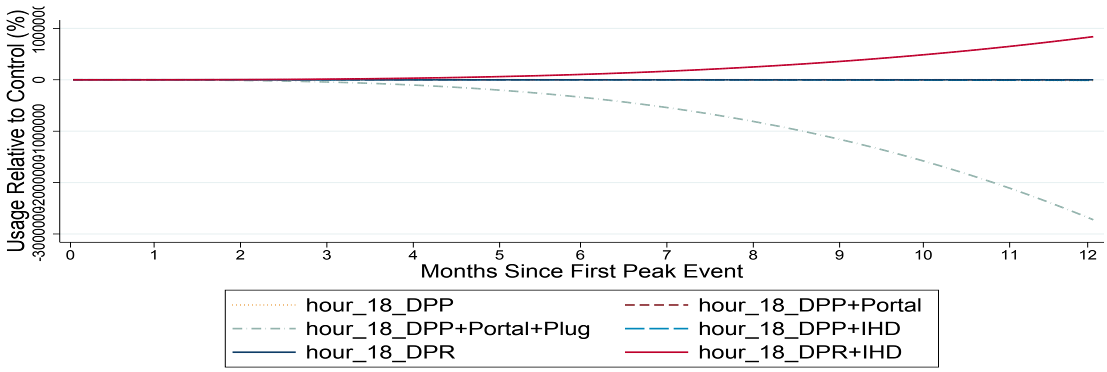

Figure B.28: Cubic Trend for Hour 1800

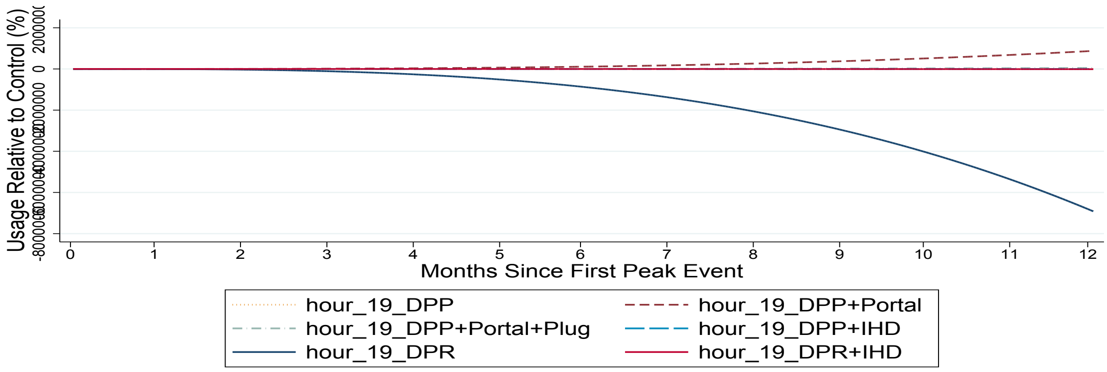

Figure B.29: Cubic Trend for Hour 1900

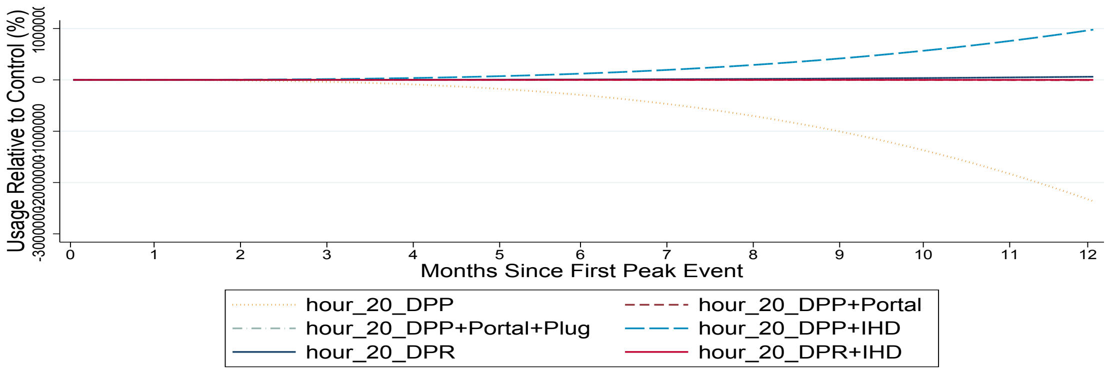

Figure B.30: Cubic Trend for Hour 2000

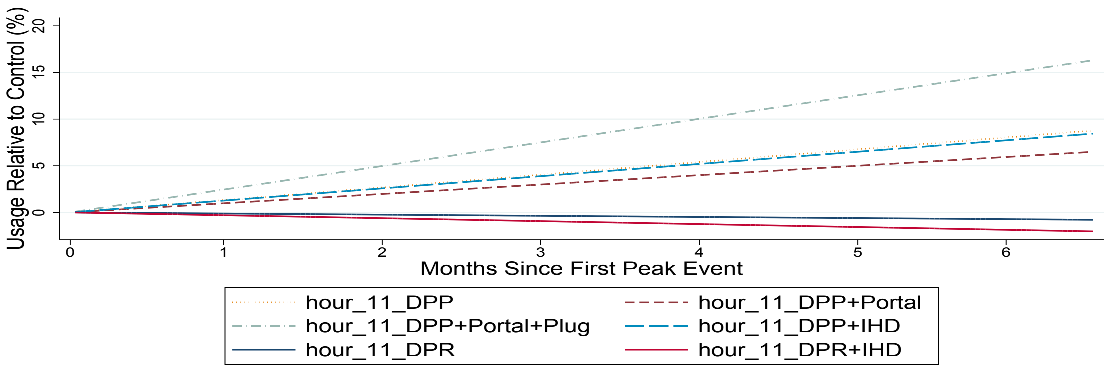

Figure B.31: Resetting Linear Trend for Hour 1100

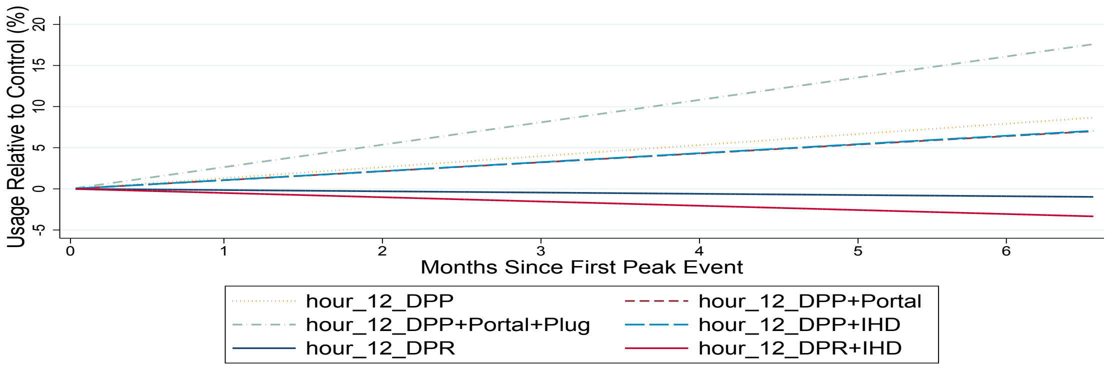

Figure B.32: Resetting Linear Trend for Hour 1200

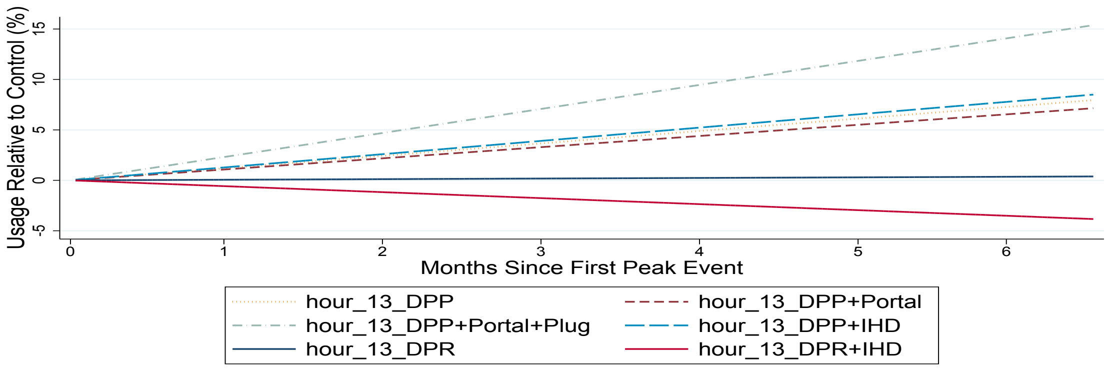

Figure B.33: Resetting Linear Trend for Hour 1300

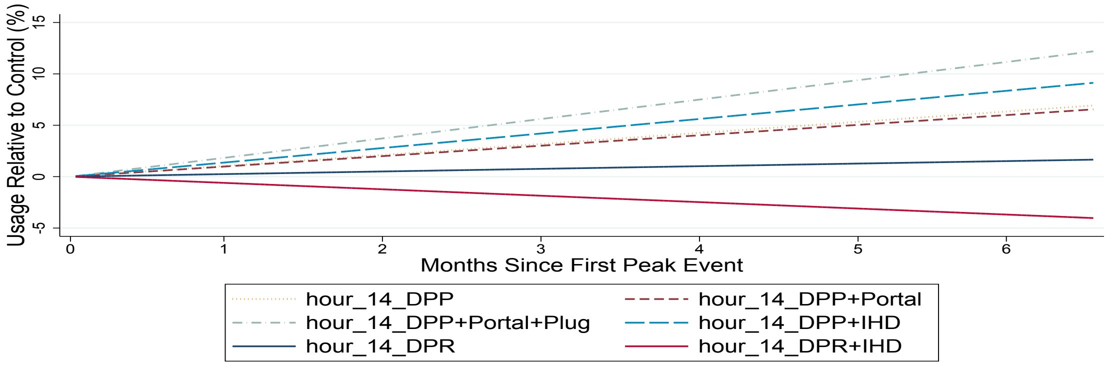

Figure B.34: Resetting Linear Trend for Hour 1400

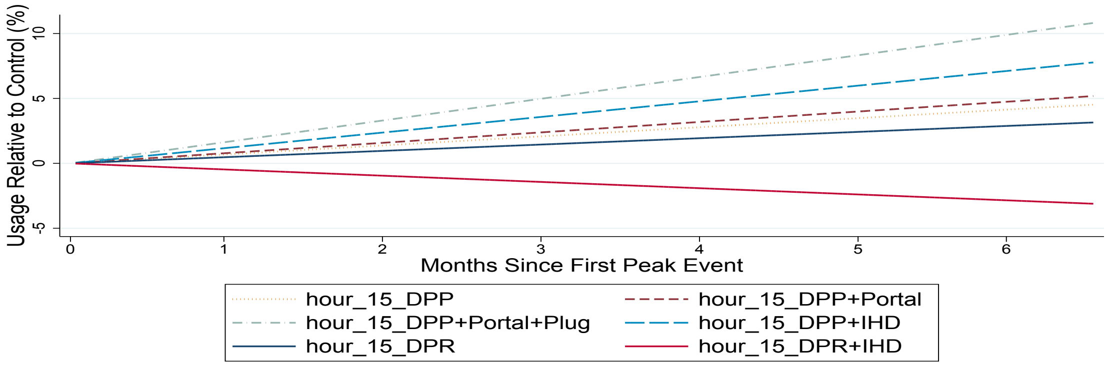

Figure B.35: Resetting Linear Trend for Hour 1500

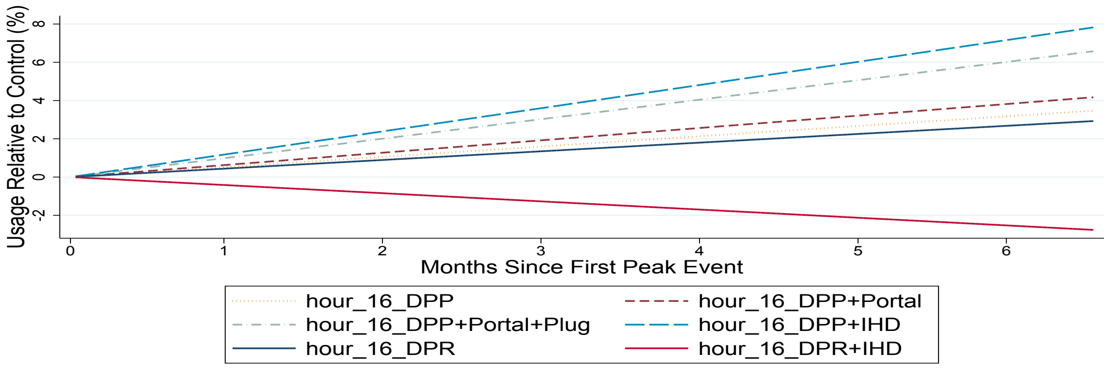

Figure B.36: Resetting Linear Trend for Hour 1600

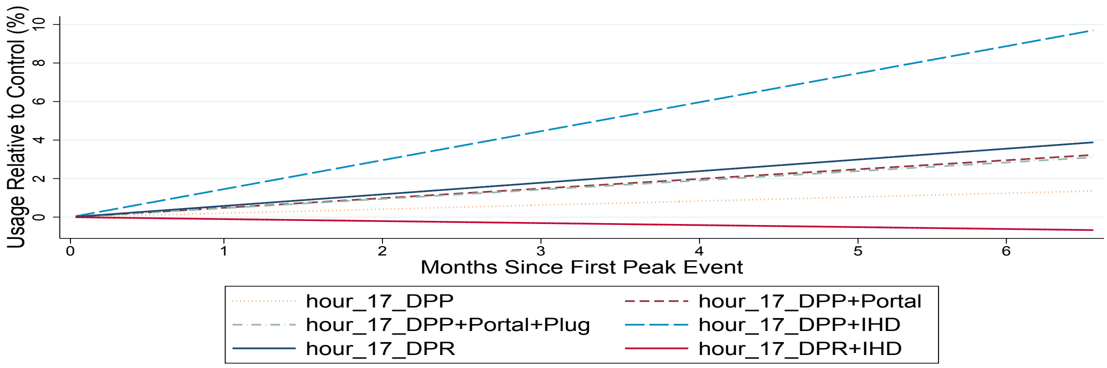

Figure B.37: Resetting Linear Trend for Hour 1700

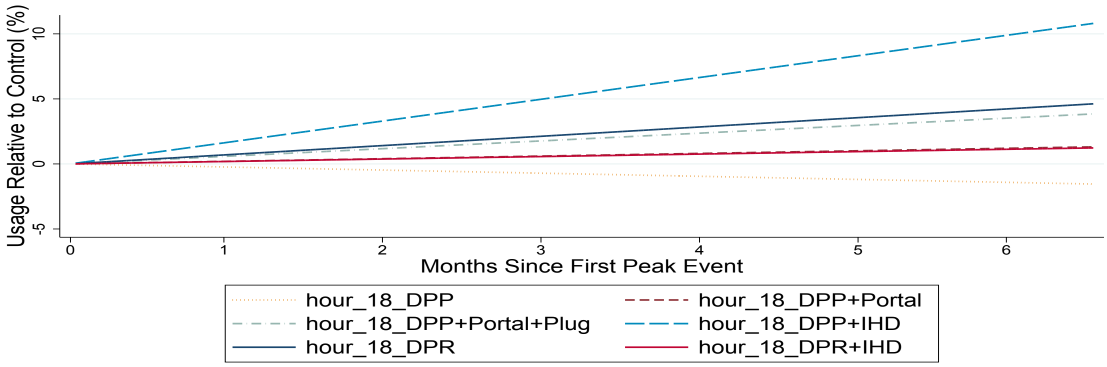

Figure B.38: Resetting Linear Trend for Hour 1800

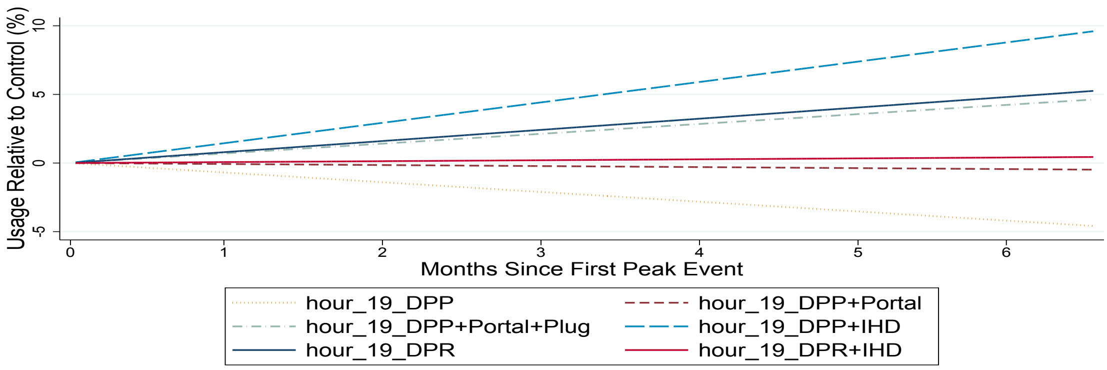

Figure B.39: Resetting Linear Trend for Hour 1900

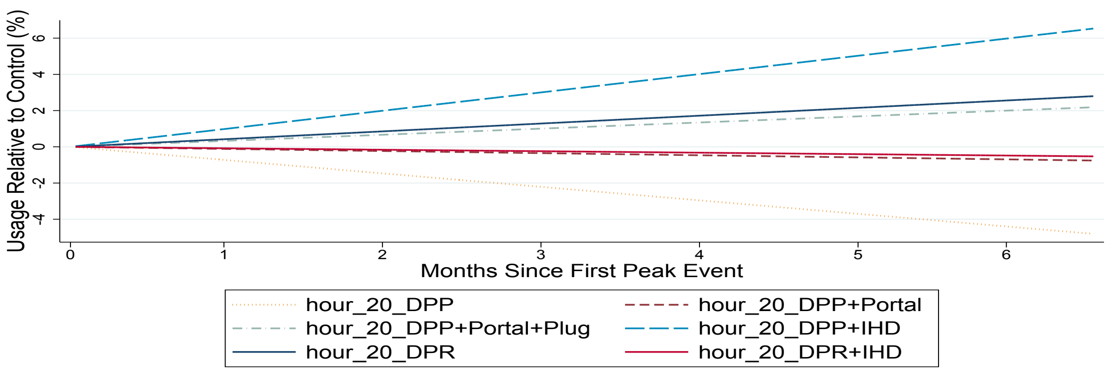

Figure B.40: Resetting Linear Trend for Hour 2000

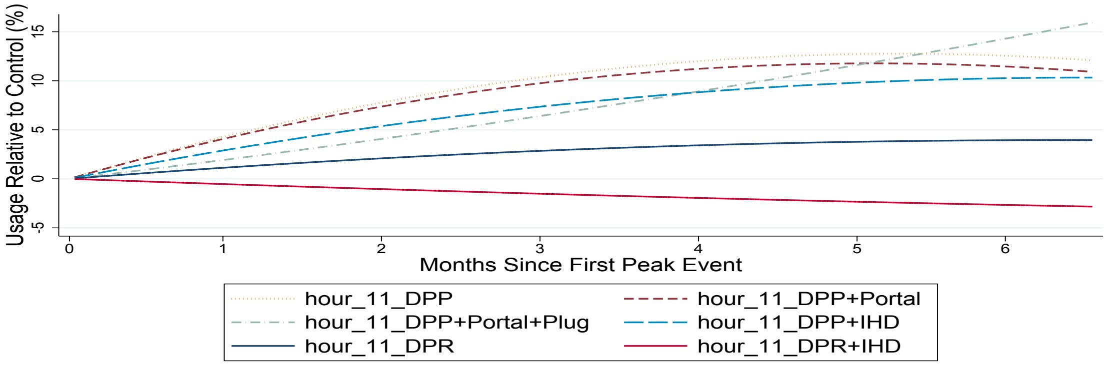

Figure B.41: Resetting Quadratic Trend for Hour 1100

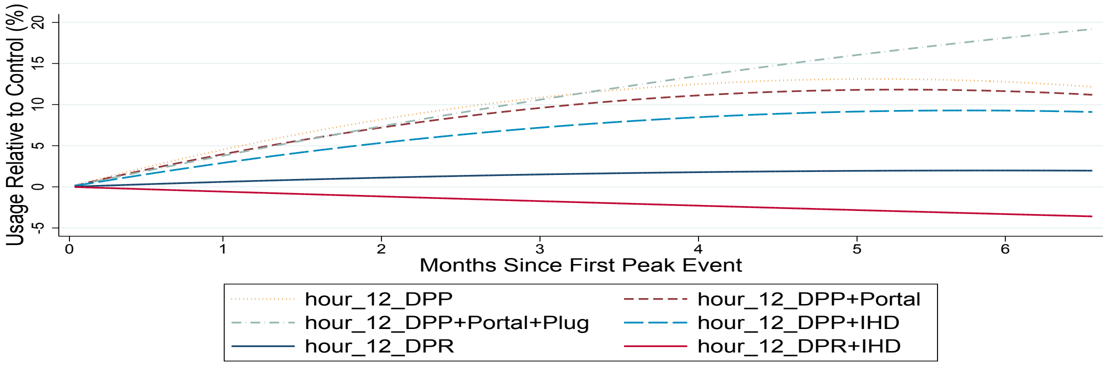

Figure B.42: Resetting Quadratic Trend for Hour 1200

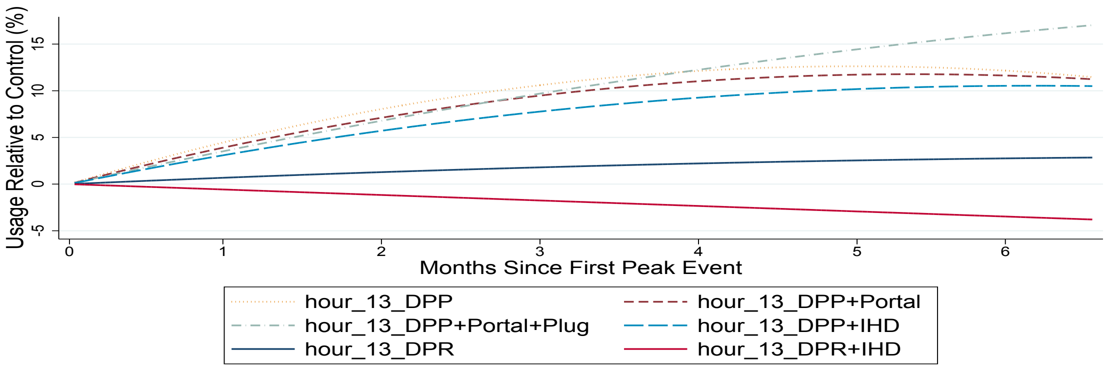

Figure B.43: Resetting Quadratic Trend for Hour 1300

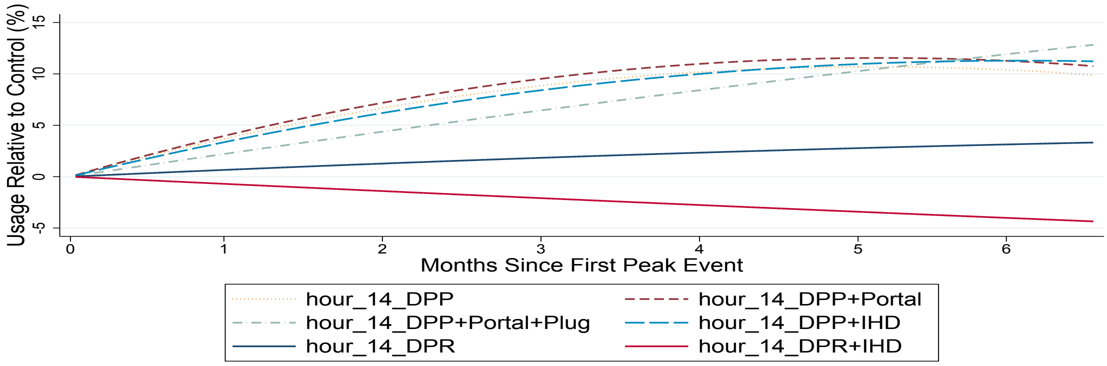

Figure B.44: Resetting Quadratic Trend for Hour 1400

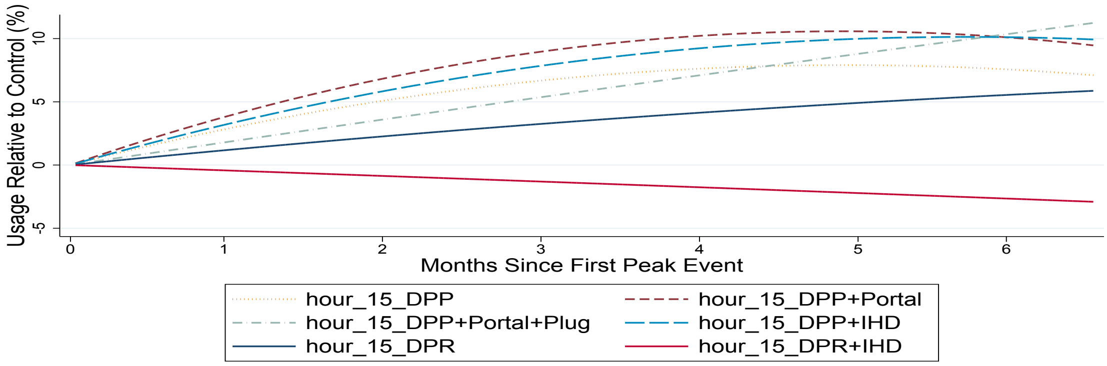

Figure B.45: Resetting Quadratic Trend for Hour 1500

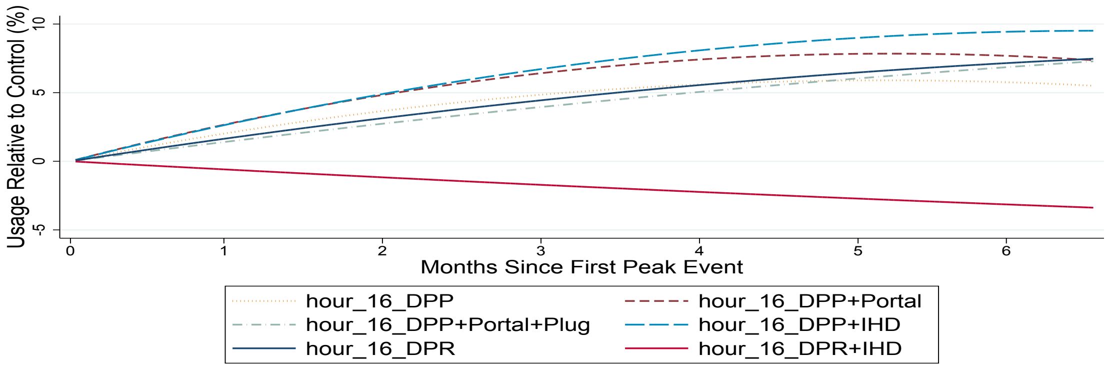

Figure B.46: Resetting Quadratic Trend for Hour 1600

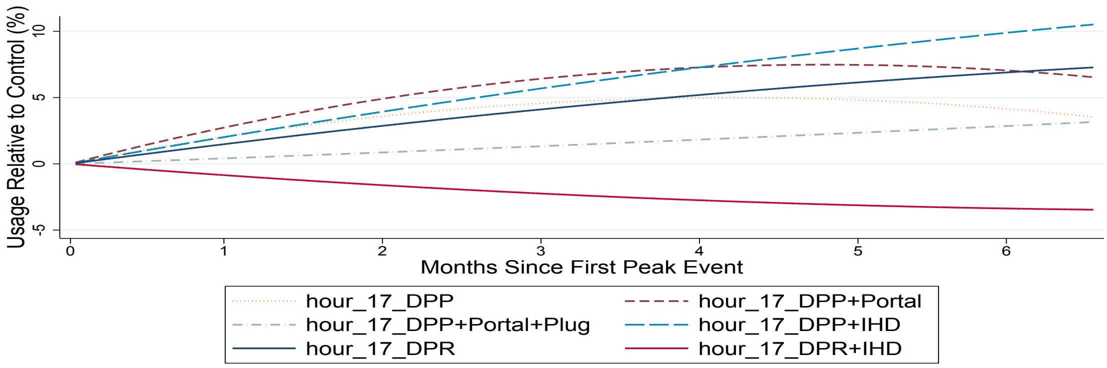

Figure B.47: Resetting Quadratic Trend for Hour 1700

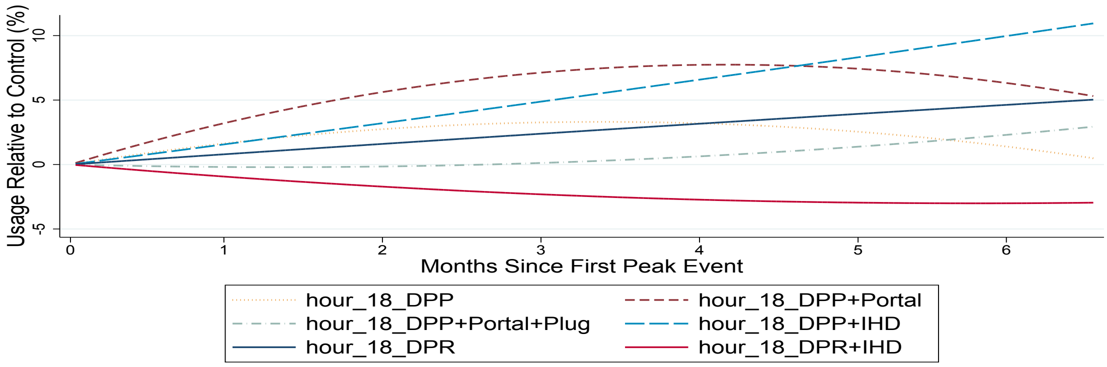

Figure B.48: Resetting Quadratic Trend for Hour 1800

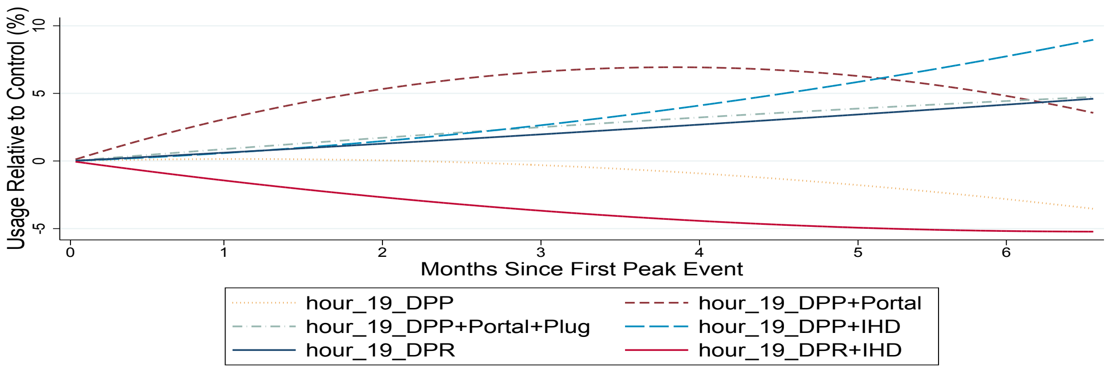

Figure B.49: Resetting Quadratic Trend for Hour 1900

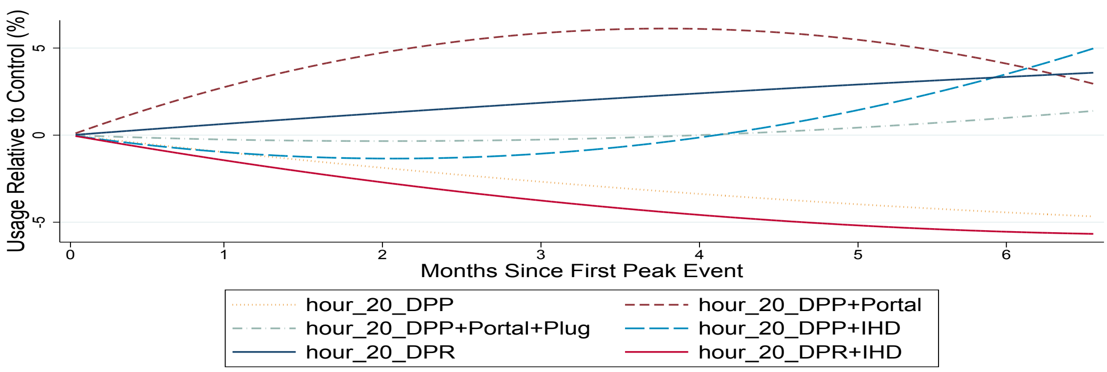

Figure B.50: Resetting Quadratic Trend for Hour 2000

B.4 Graphs and Tables of Habit Formation - Sub-samples

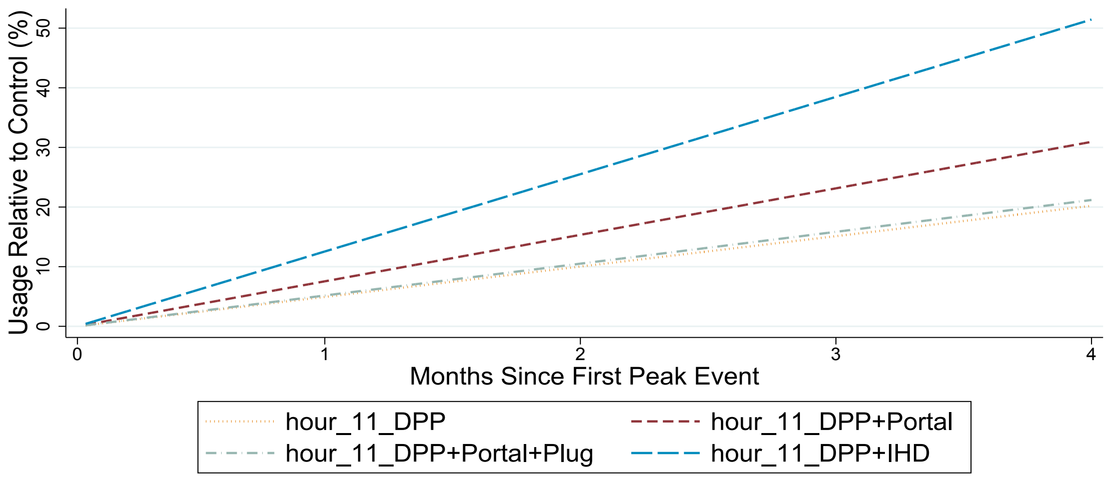

Figure B.51: DPP Trend for Hour 1100

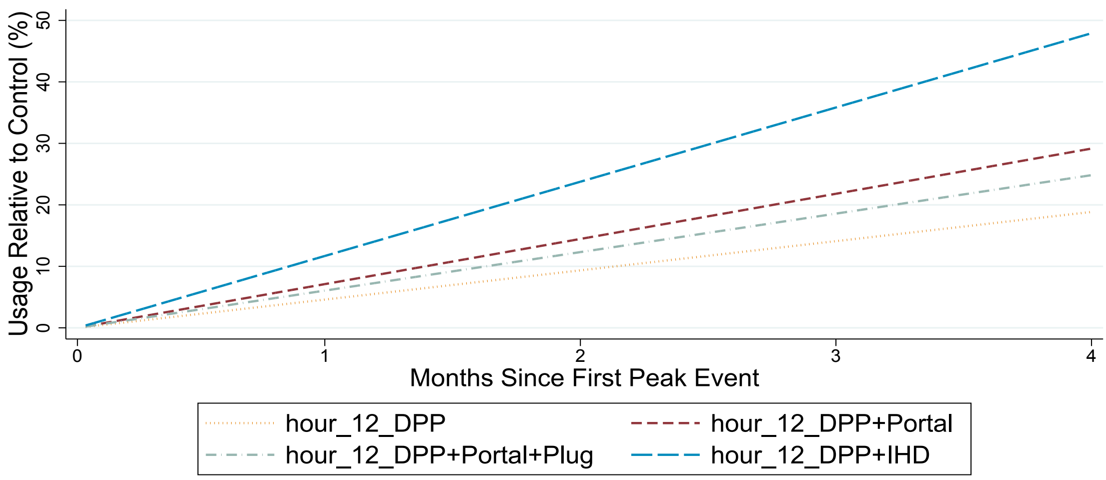

Figure B.52: DPP Trend for Hour 1200

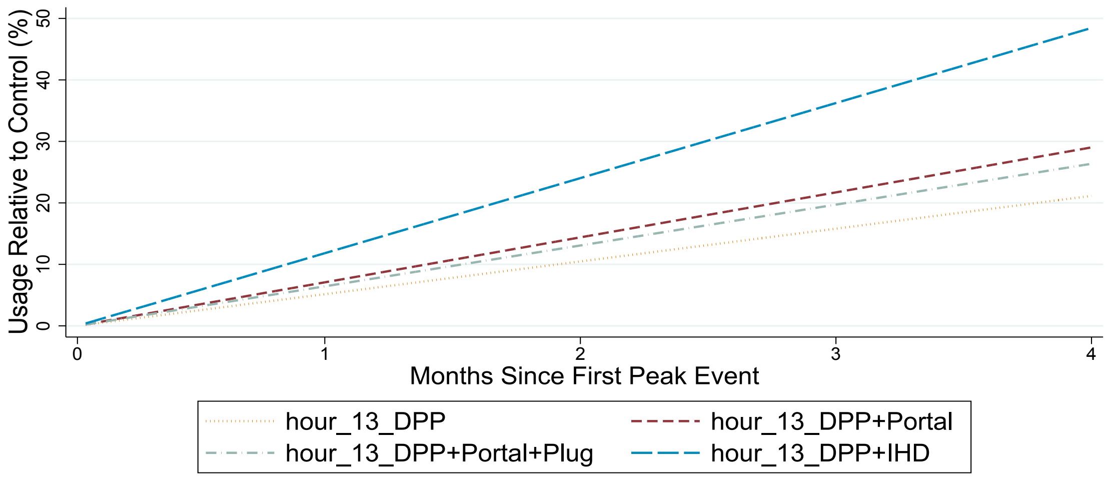

Figure B.53: DPP Trend for Hour 1300

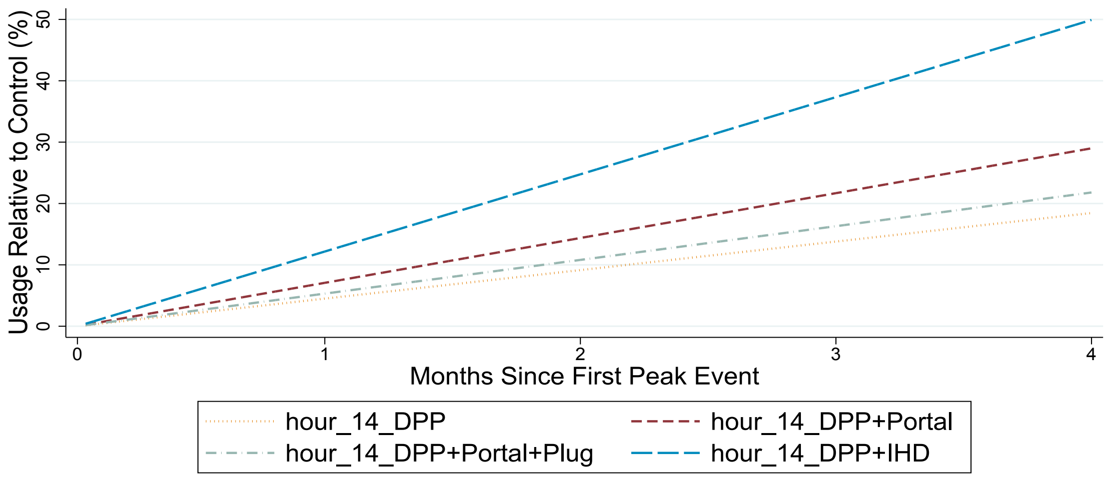

Figure B.54: DPP Trend for Hour 1400

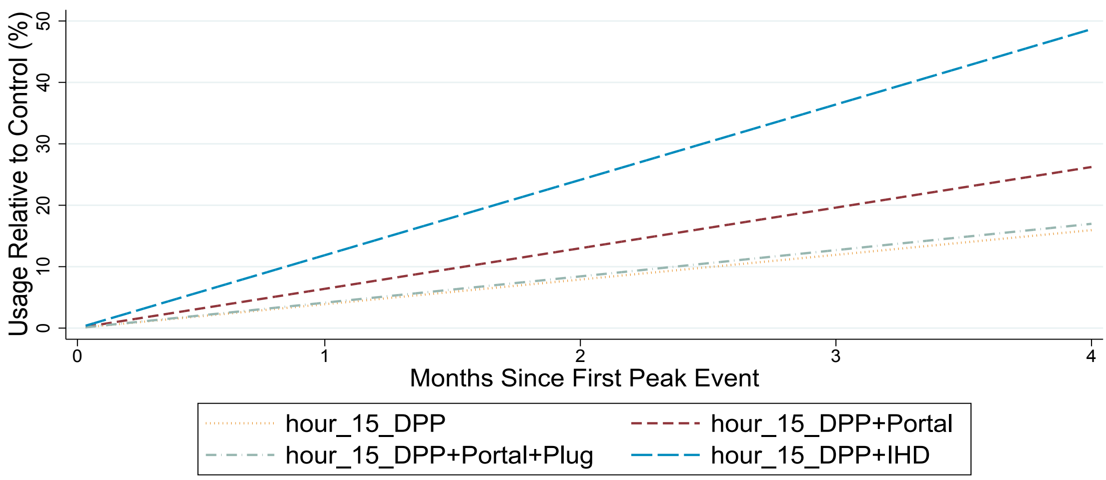

Figure B.55: DPP Trend for Hour 1500

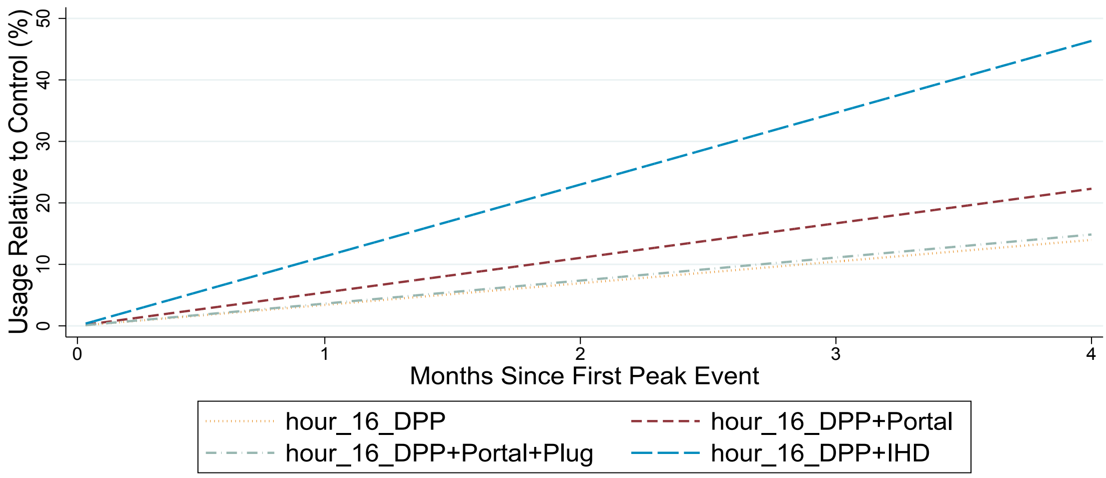

Figure B.56: DPP Trend for Hour 1600

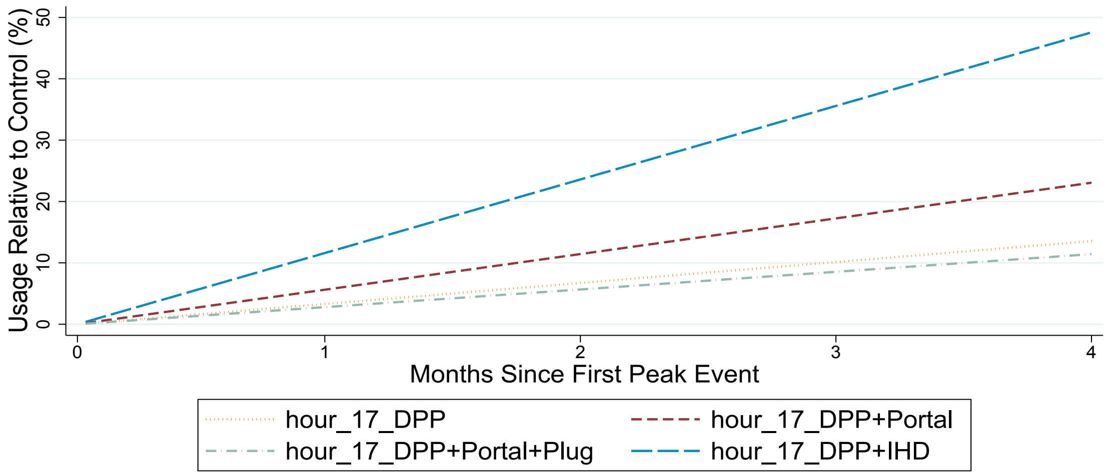

Figure B.57: DPP Trend for Hour 1700

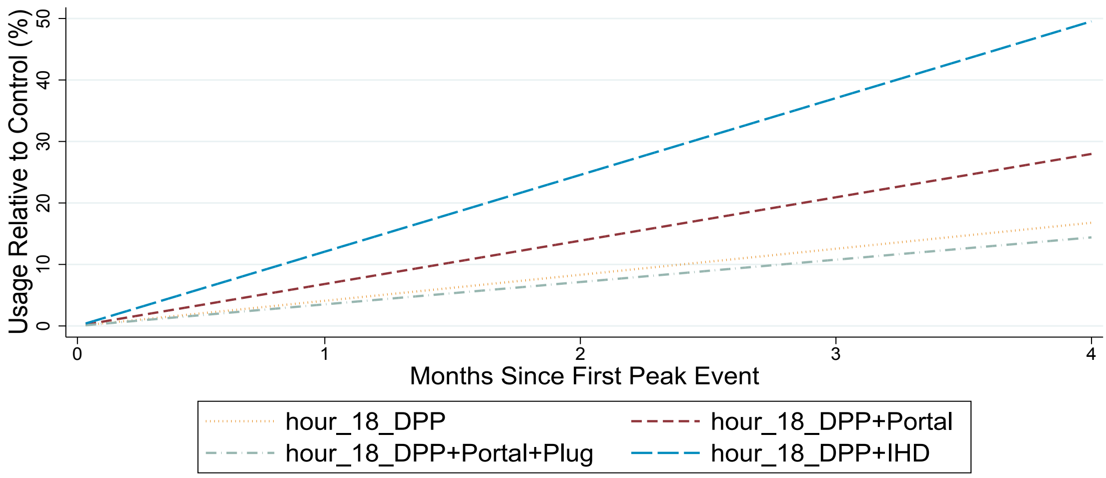

Figure B.58: DPP Trend for Hour 1800

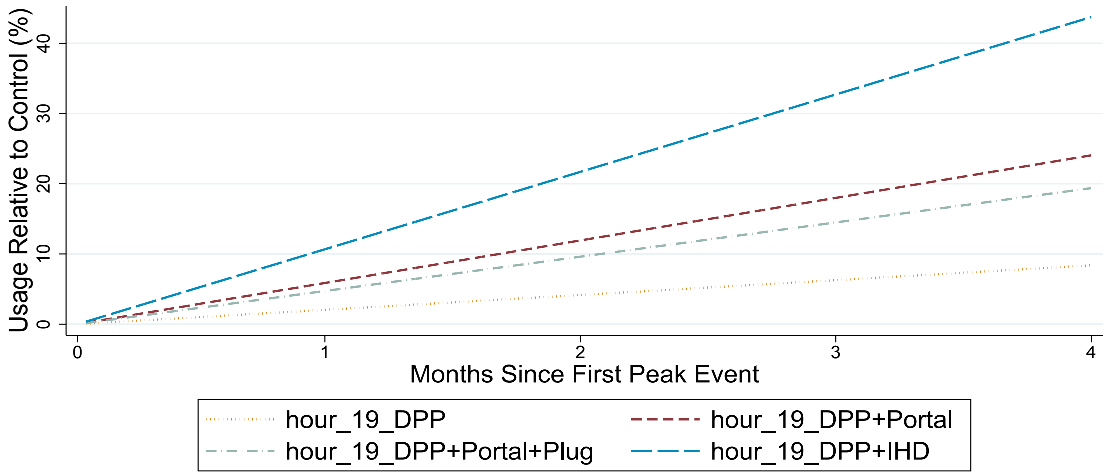

Figure B.59: DPP Trend for Hour 1900

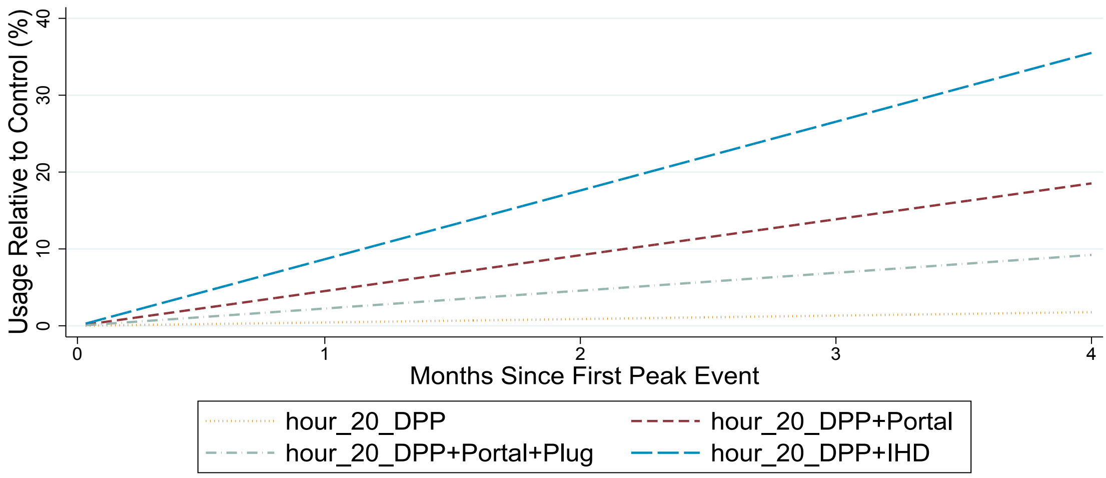

Figure B.60: DPP Trend for Hour 2000

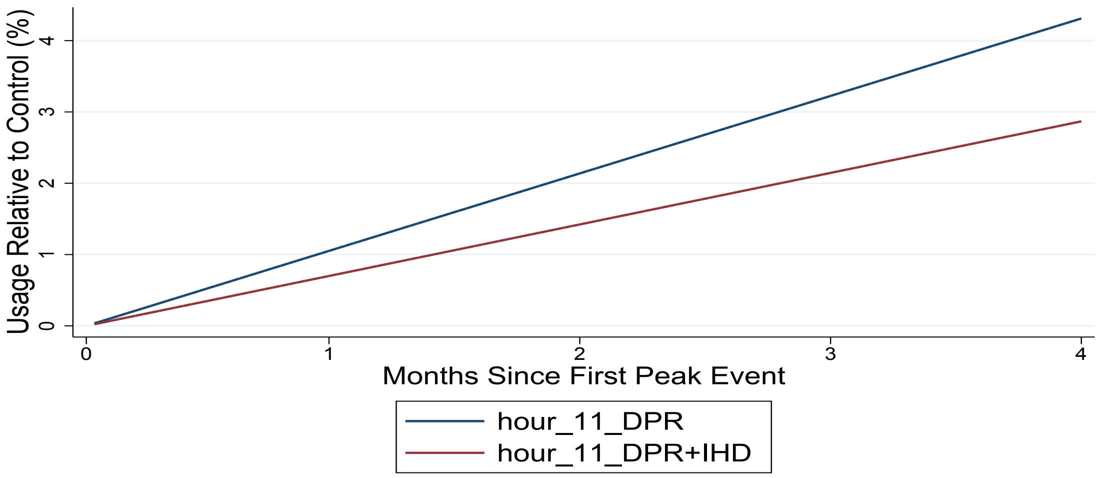

Figure B.61: DPR1 Linear Trend for Hour 1100

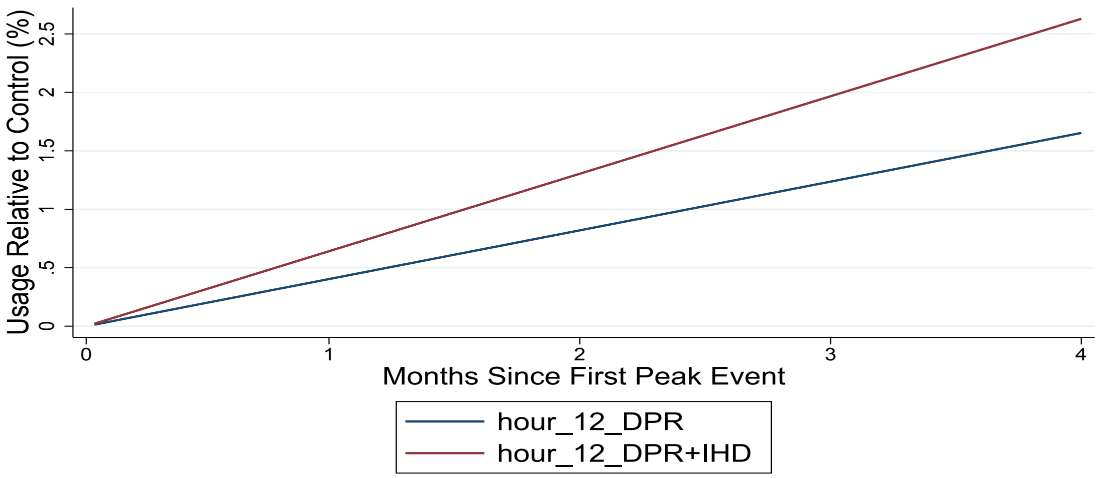

Figure B.62: DPR1 Linear Trend for Hour 1200

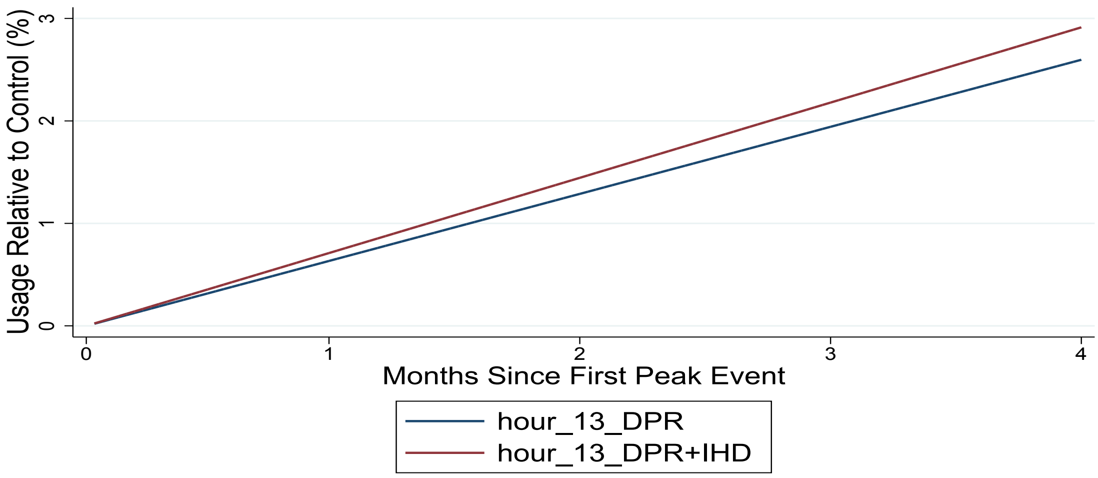

Figure B.63: DPR1 Linear Trend for Hour 1300

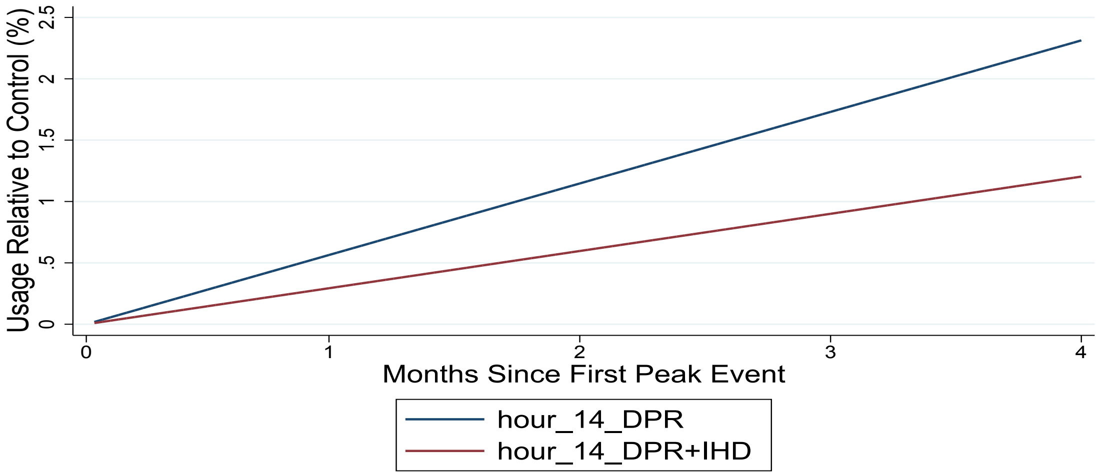

Figure B.64: DPR1 Linear Trend for Hour 1400

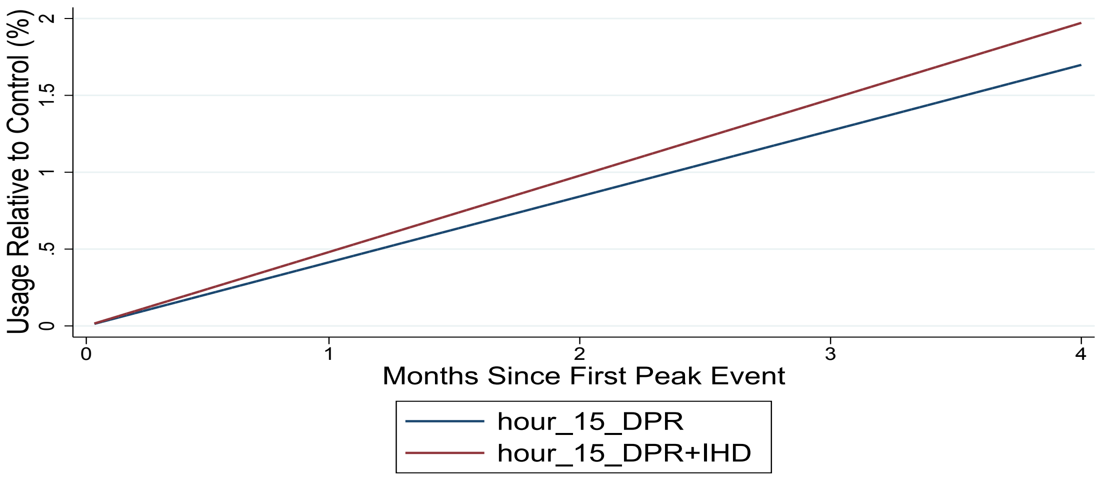

Figure B.65: DPR1 Linear Trend for Hour 1500

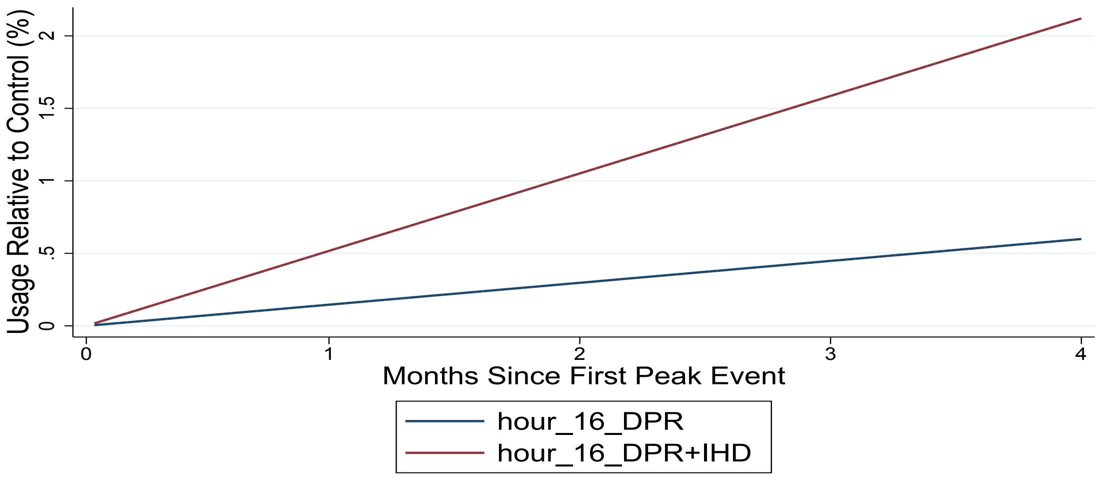

Figure B.66: DPR1 Linear Trend for Hour 1600

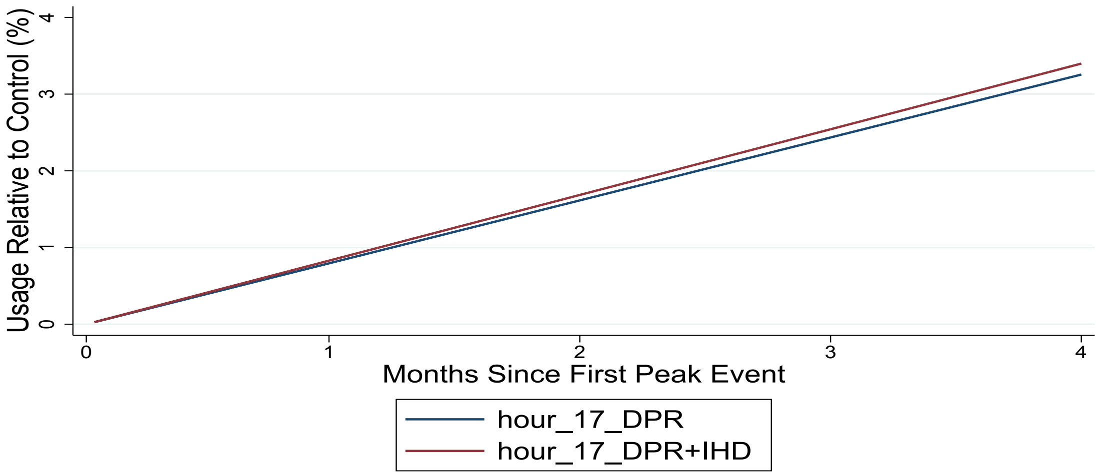

Figure B.67: DPR1 Linear Trend for Hour 1700

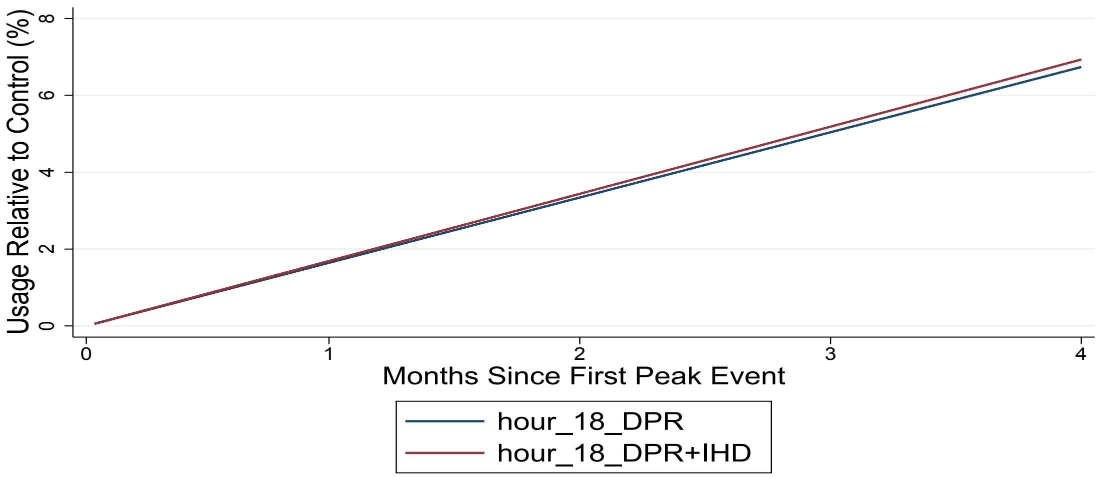

Figure B.68: DPR1 Linear Trend for Hour 1800

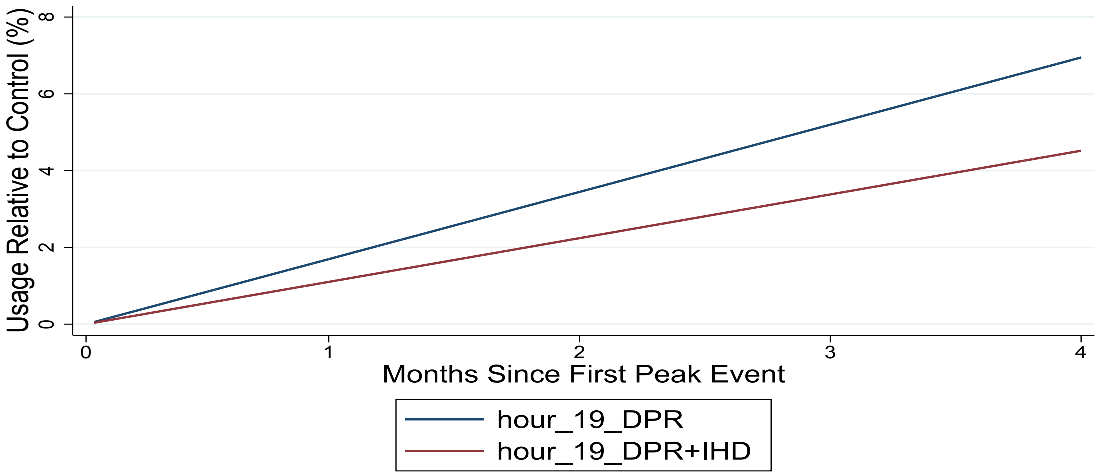

Figure B.69: DPR1 Linear Trend for Hour 1900

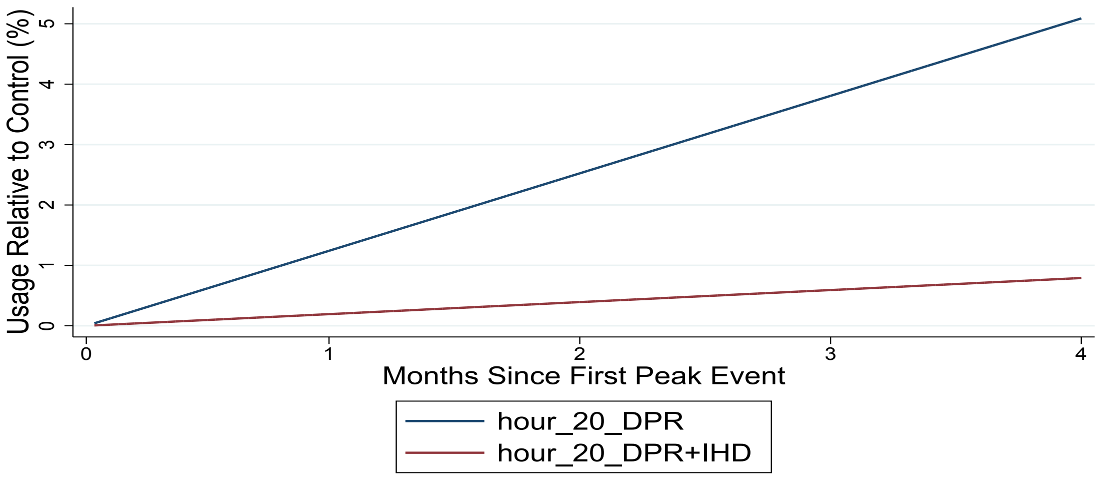

Figure B.70: DPR1 Linear Trend for Hour 2000

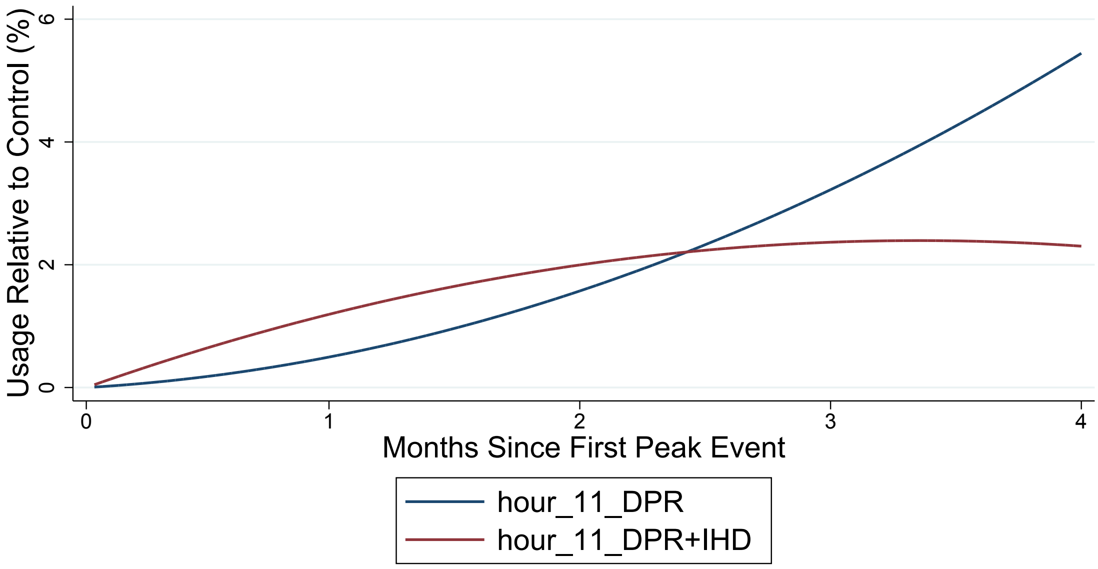

Figure B.71: DPR1 Quadratic Trend for Hour 1100

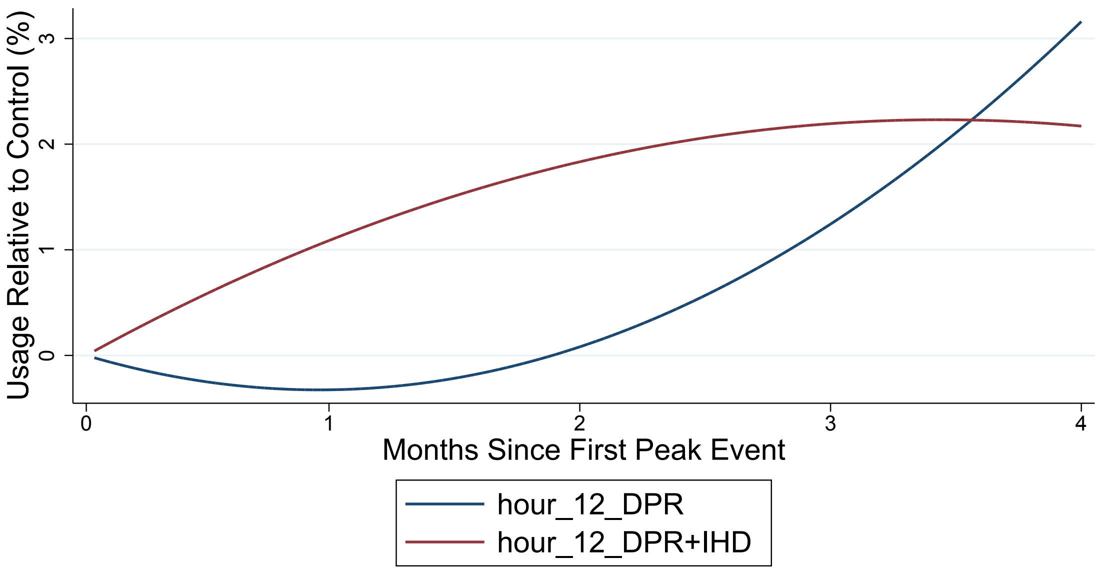

Figure B.72: DPR1 Quadratic Trend for Hour 1200

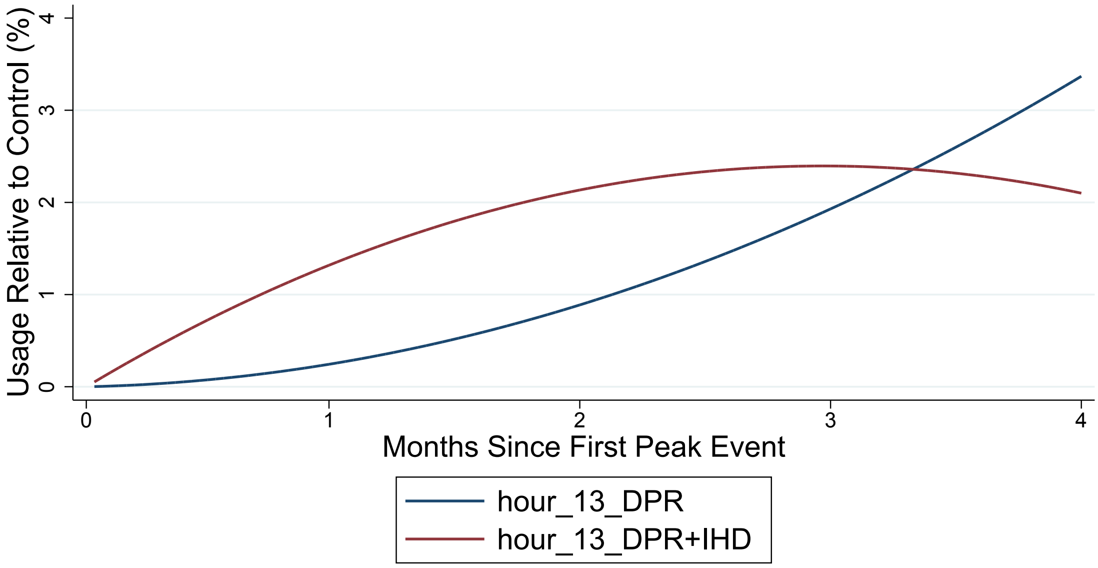

Figure B.73: DPR1 Quadratic Trend for Hour 1300

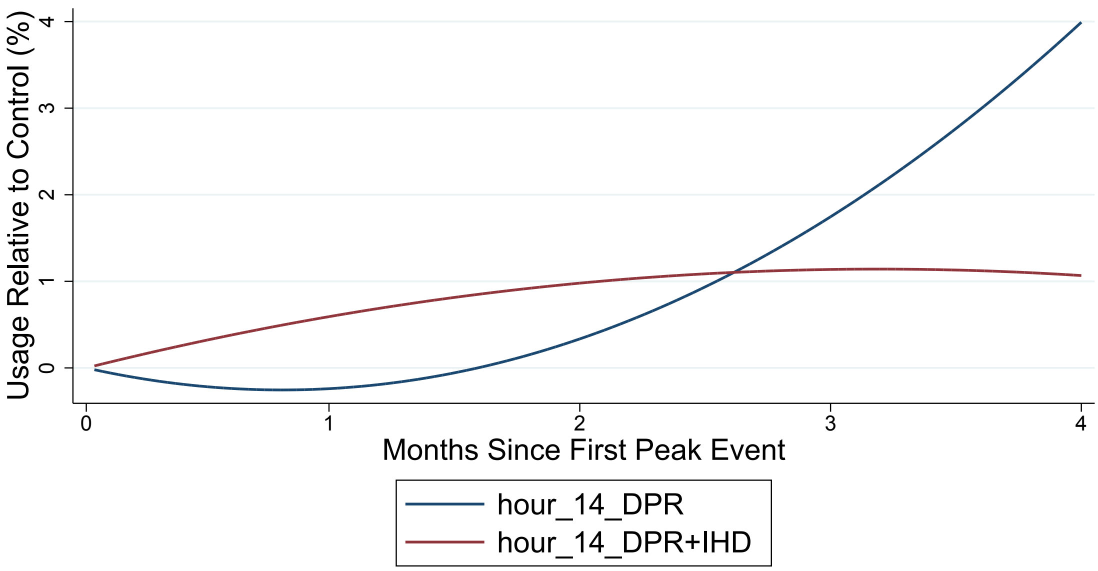

Figure B.74: DPR1 Quadratic Trend for Hour 1400

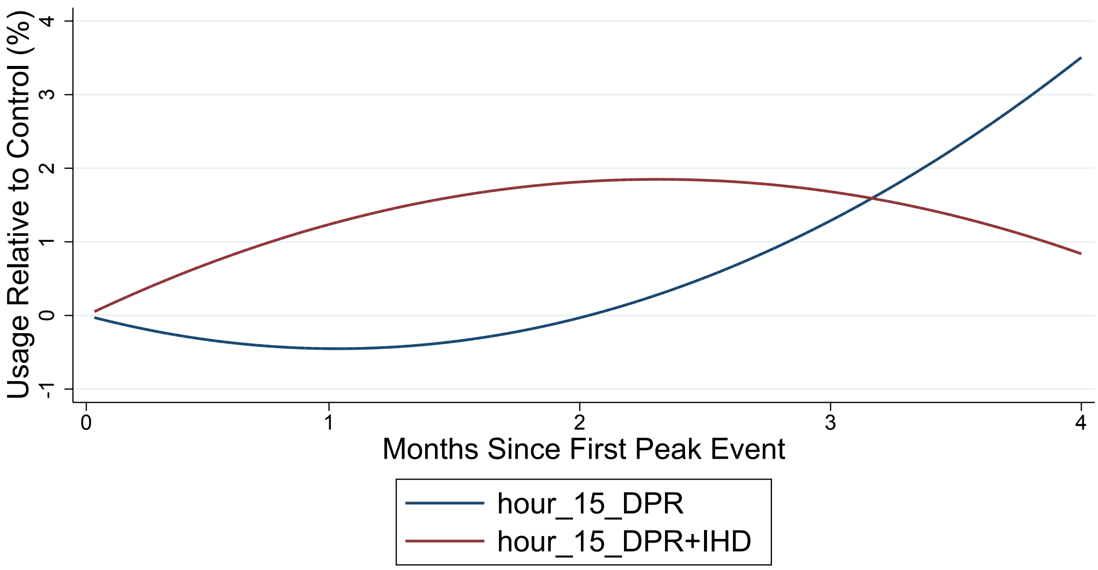

Figure B.75: DPR1 Quadratic Trend for Hour 1500

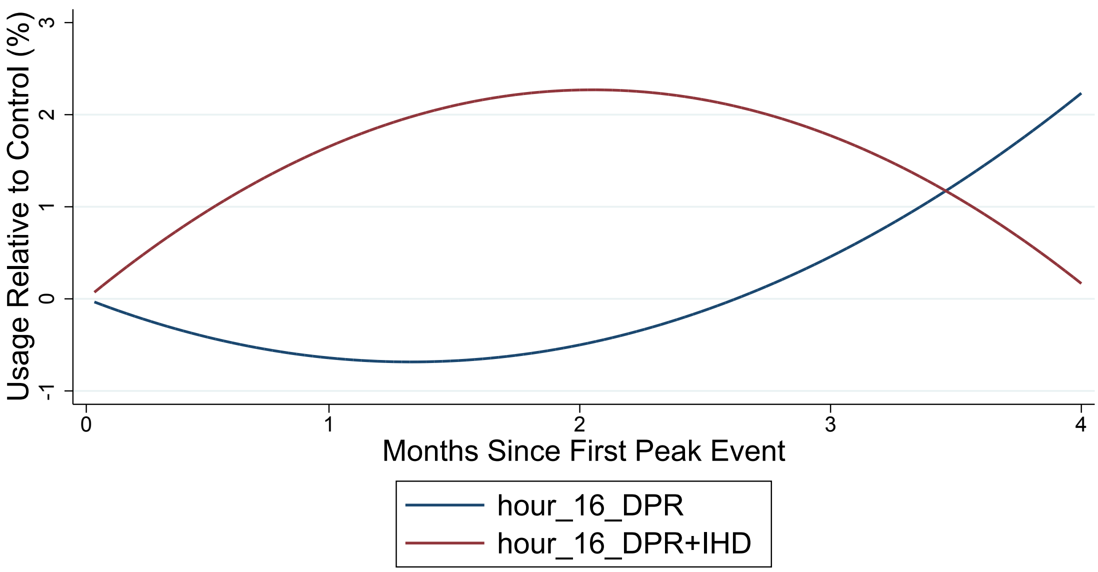

Figure B.76: DPR1 Quadratic Trend for Hour 1600

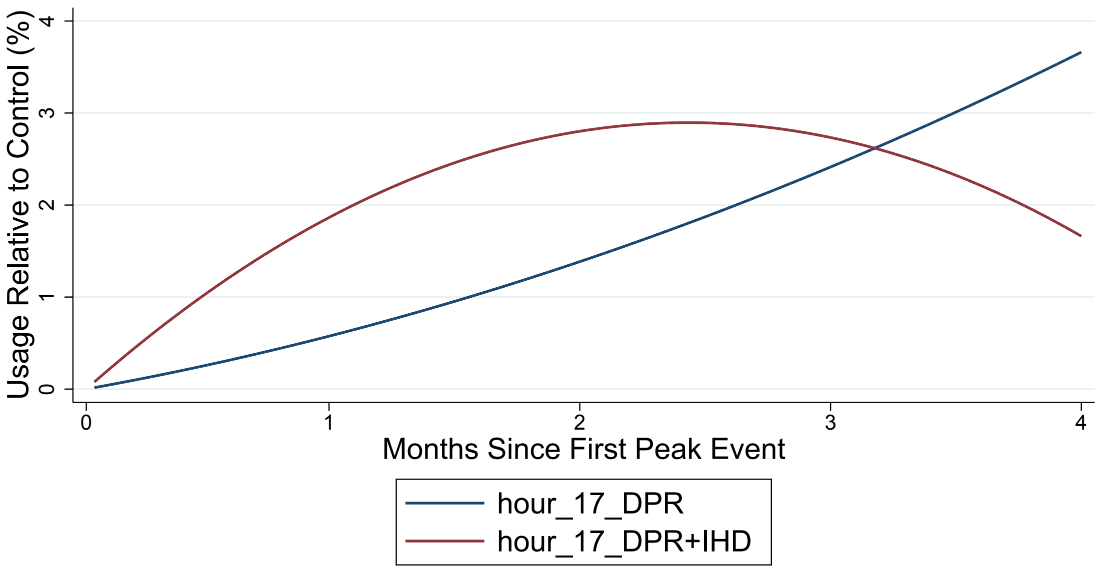

Figure B.77: DPR1 Quadratic Trend for Hour 1700

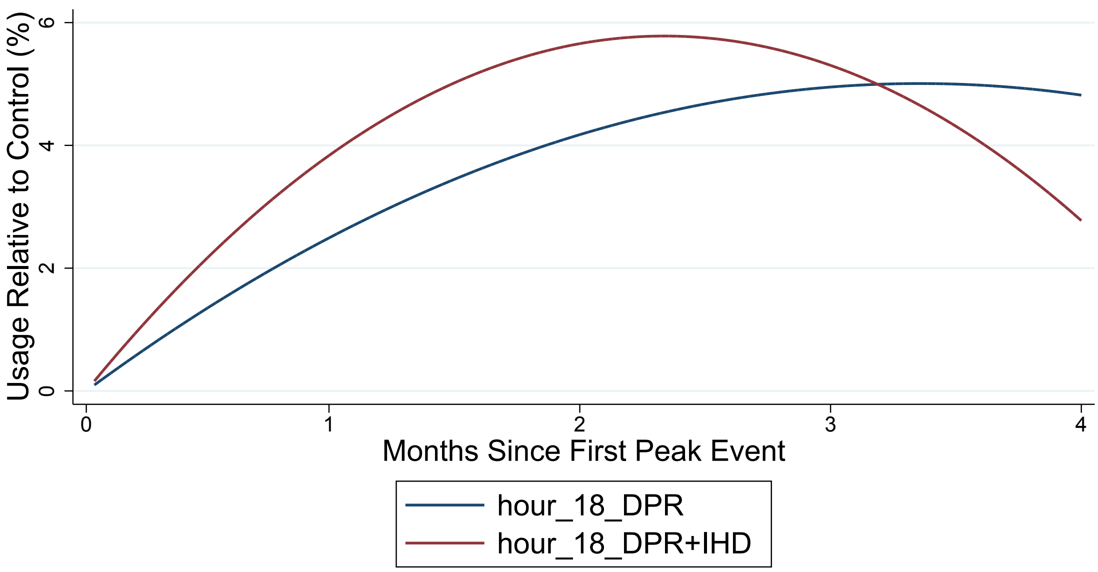

Figure B.78: DPR1 Quadratic Trend for Hour 1800

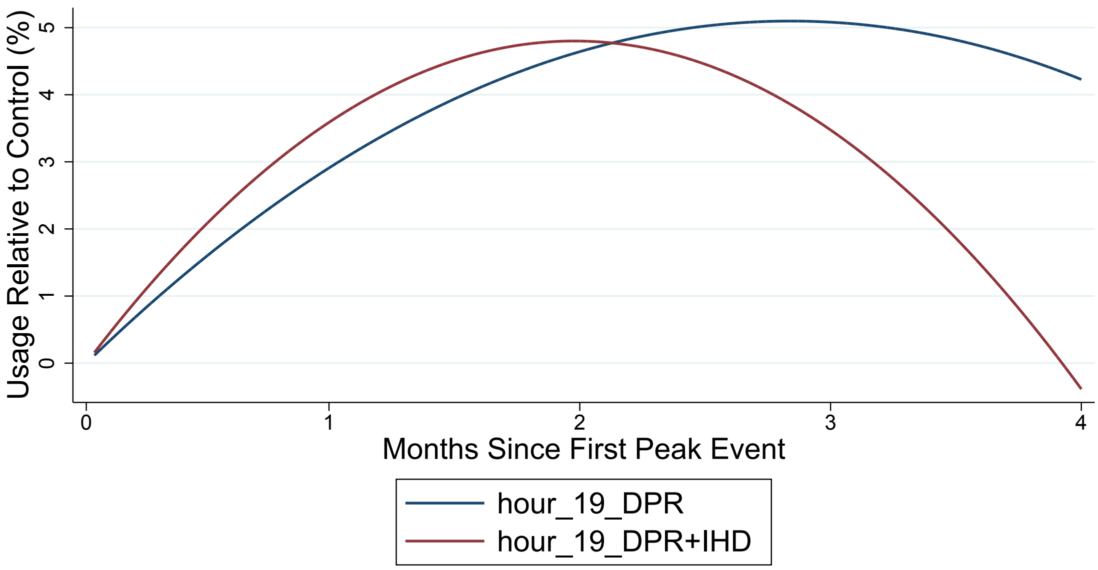

Figure B.79: DPR1 Quadratic Trend for Hour 1900

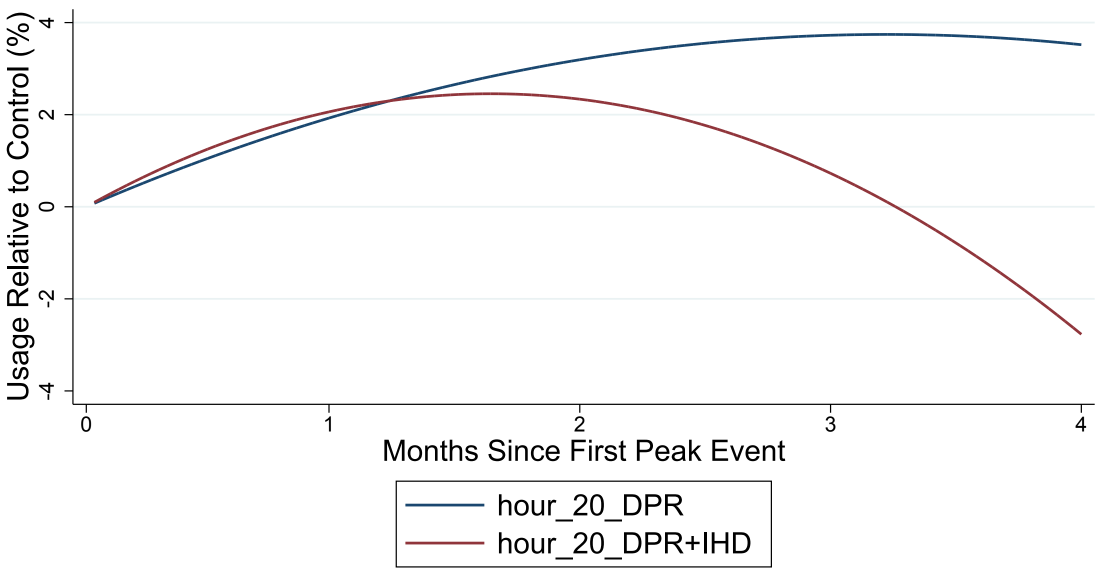

Figure B.80: DPR1 Quadratic Trend for Hour 2000

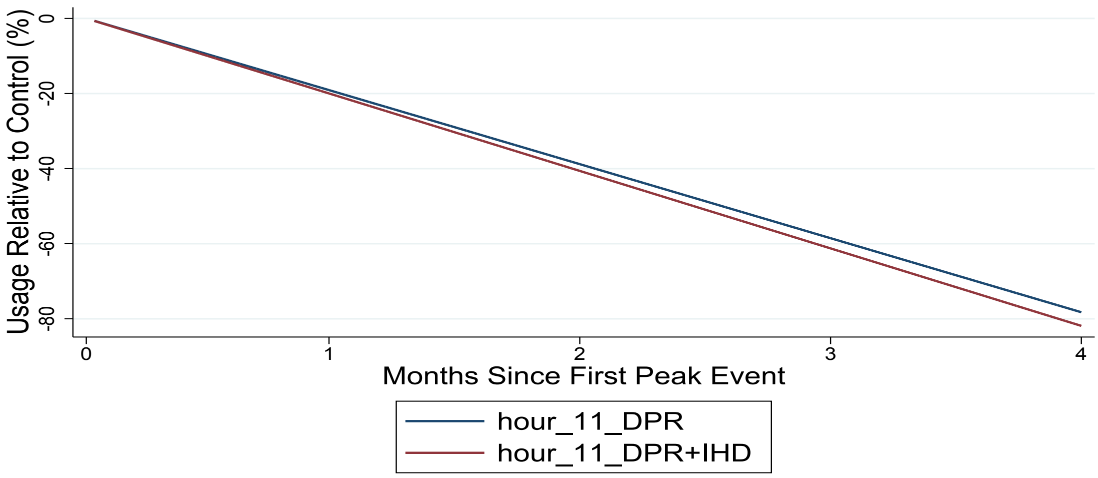

Figure B.81: DPR2 Linear Trend for Hour 1100

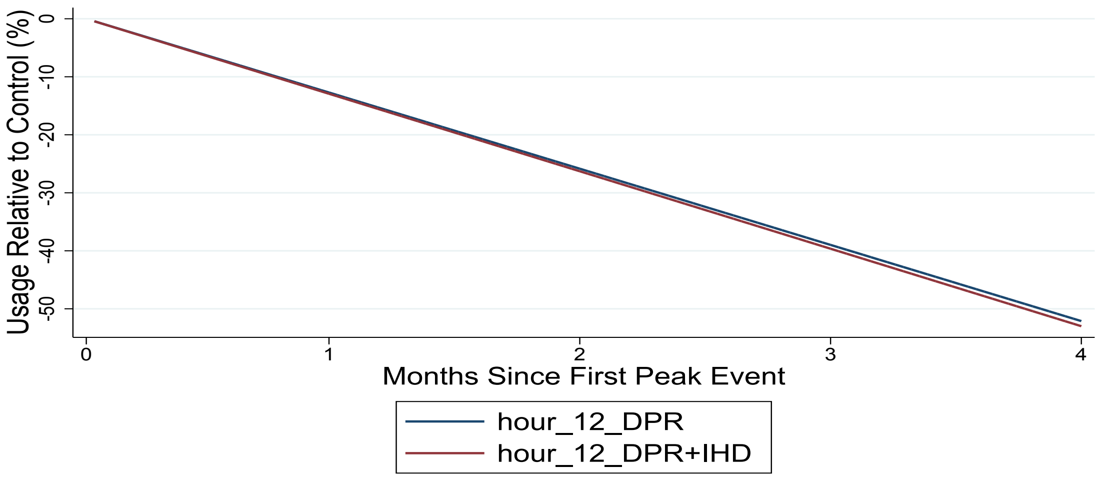

Figure B.82: DPR2 Linear Trend for Hour 1200

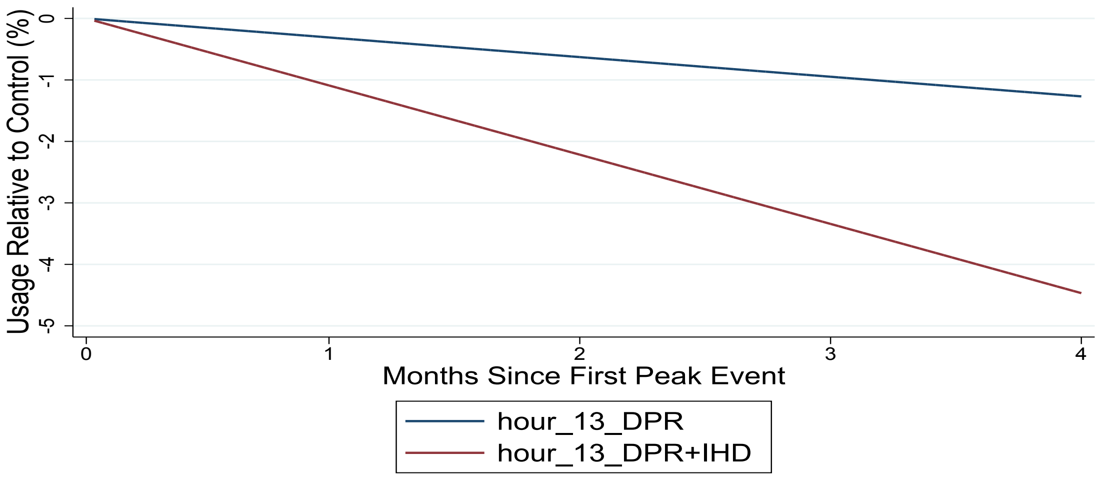

Figure B.83: DPR2 Linear Trend for Hour 1300

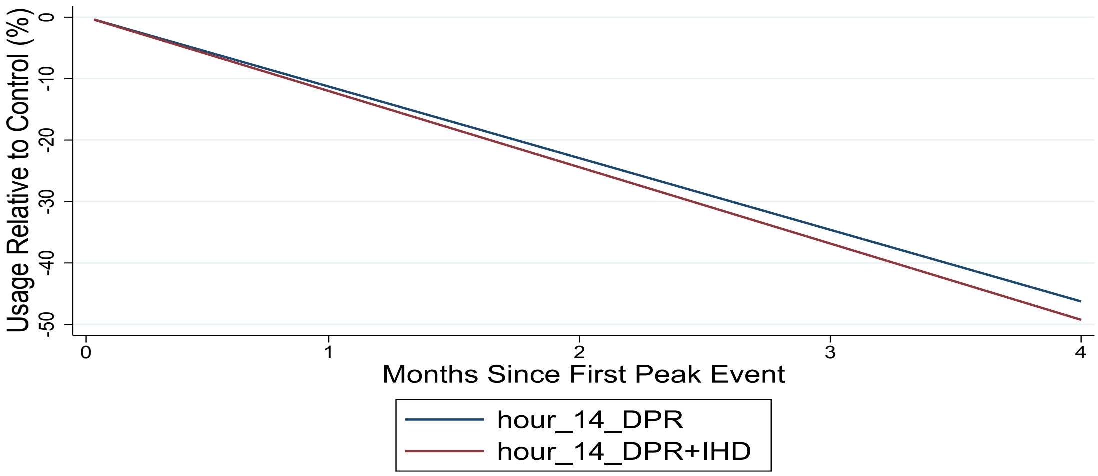

Figure B.84: DPR2 Linear Trend for Hour 1400

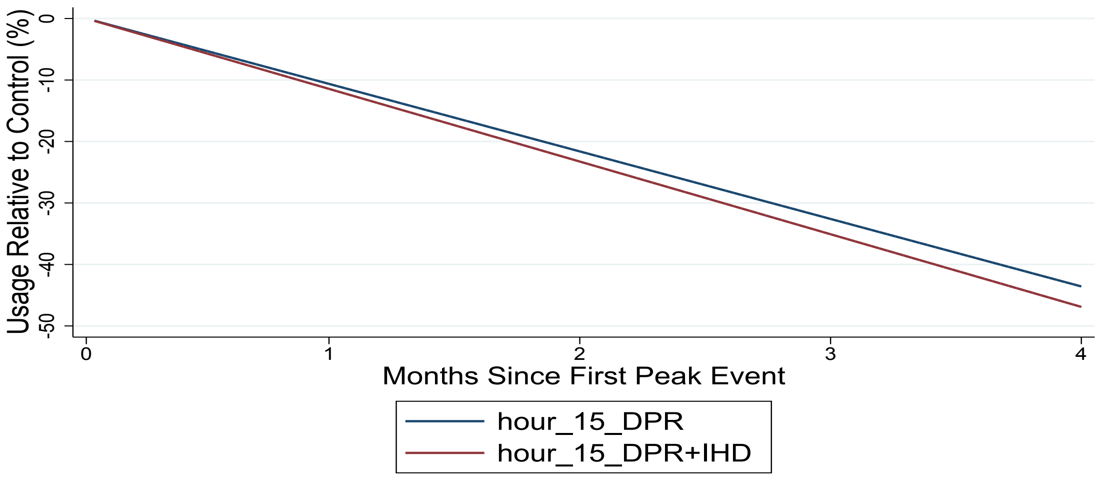

Figure B.85: DPR2 Linear Trend for Hour 1500

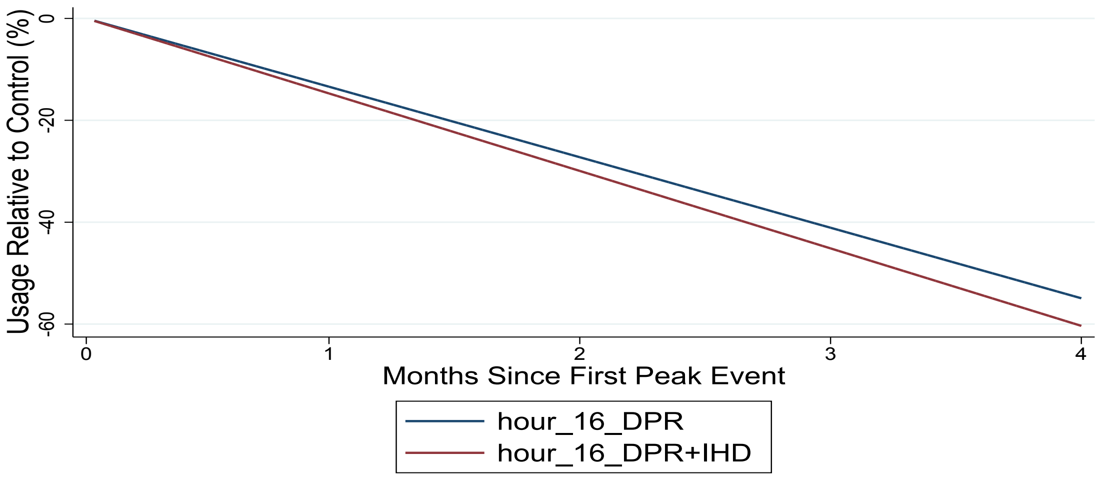

Figure B.86: DPR2 Linear Trend for Hour 1600

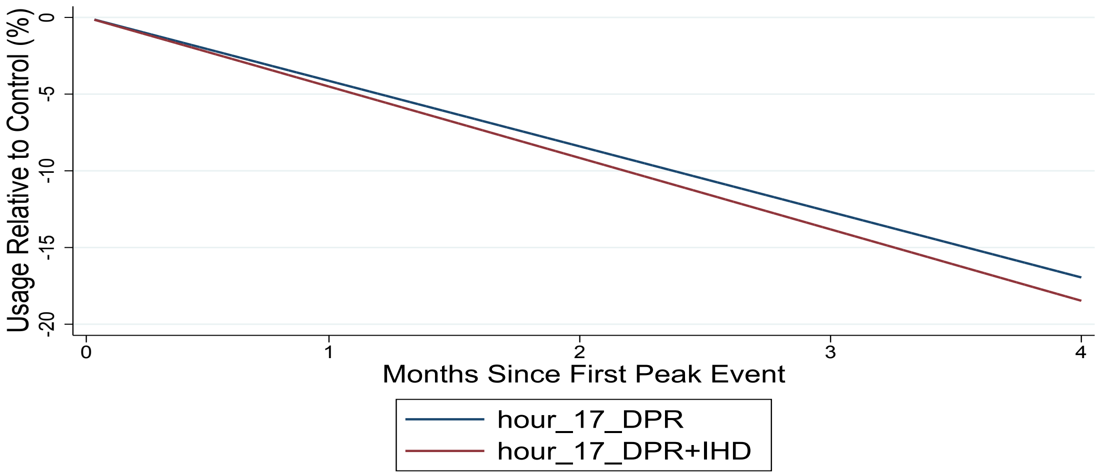

Figure B.87: DPR2 Linear Trend for Hour 1700

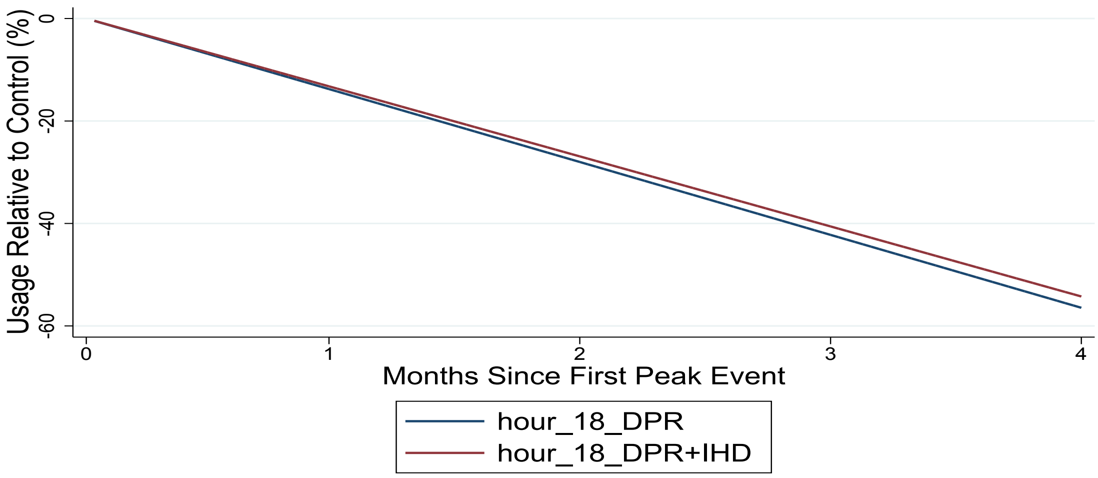

Figure B.88: DPR2 Linear Trend for Hour 1800

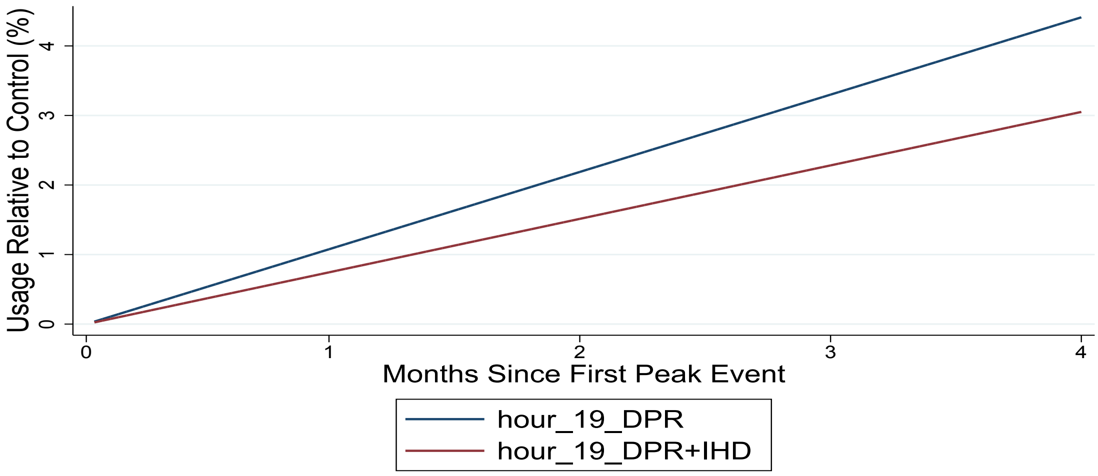

Figure B.89: DPR2 Linear Trend for Hour 1900

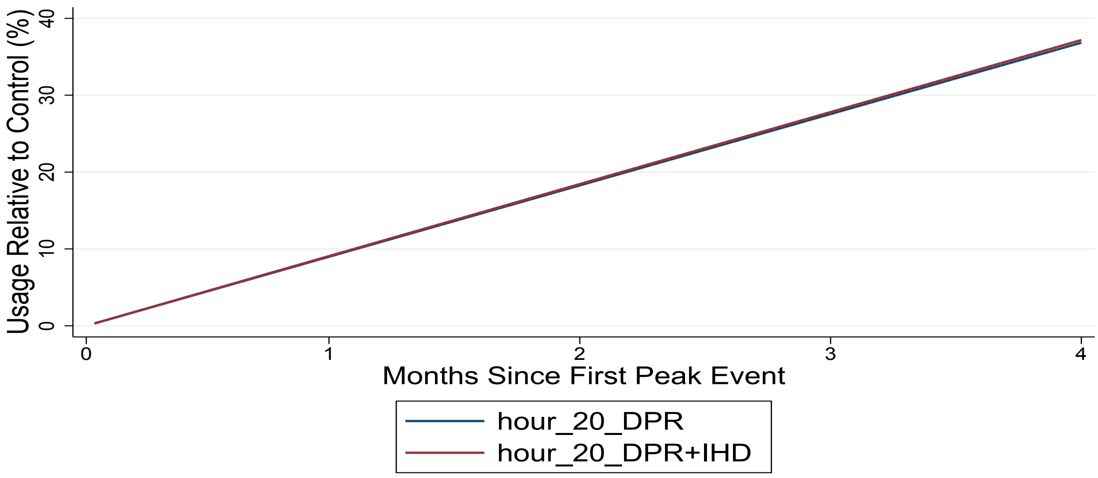

Figure B.90: DPR2 Linear Trend for Hour 2000

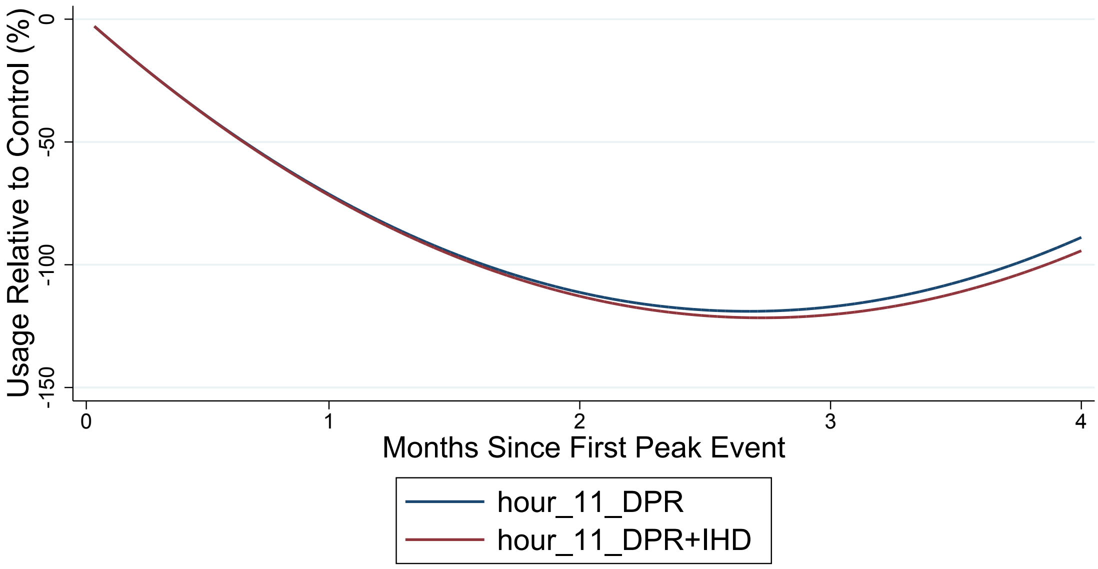

Figure B.91: DPR2 Quadratic Trend for Hour 1100

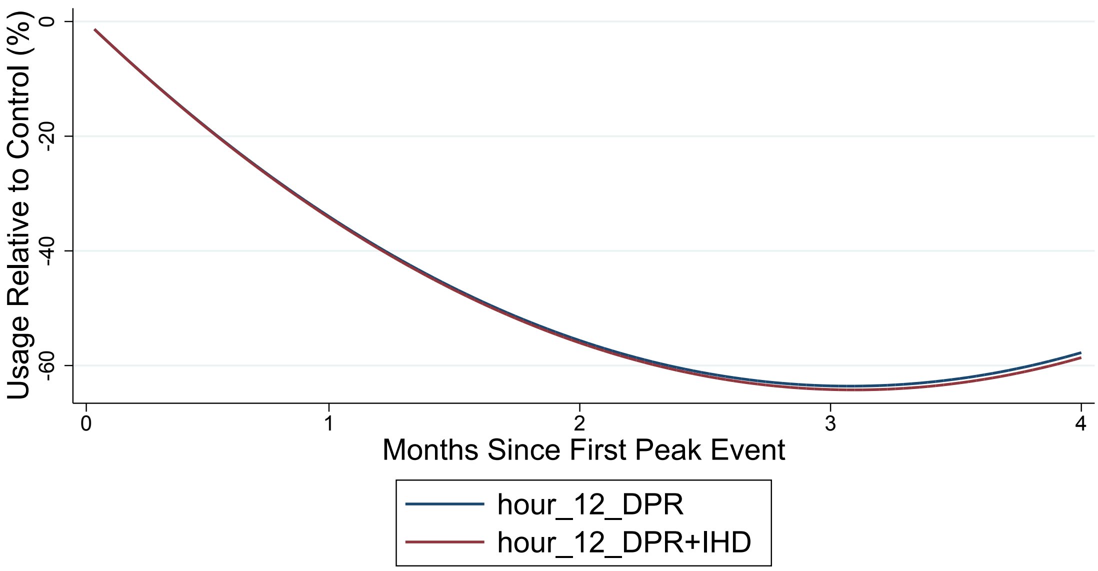

Figure B.92: DPR2 Quadratic Trend for Hour 1200

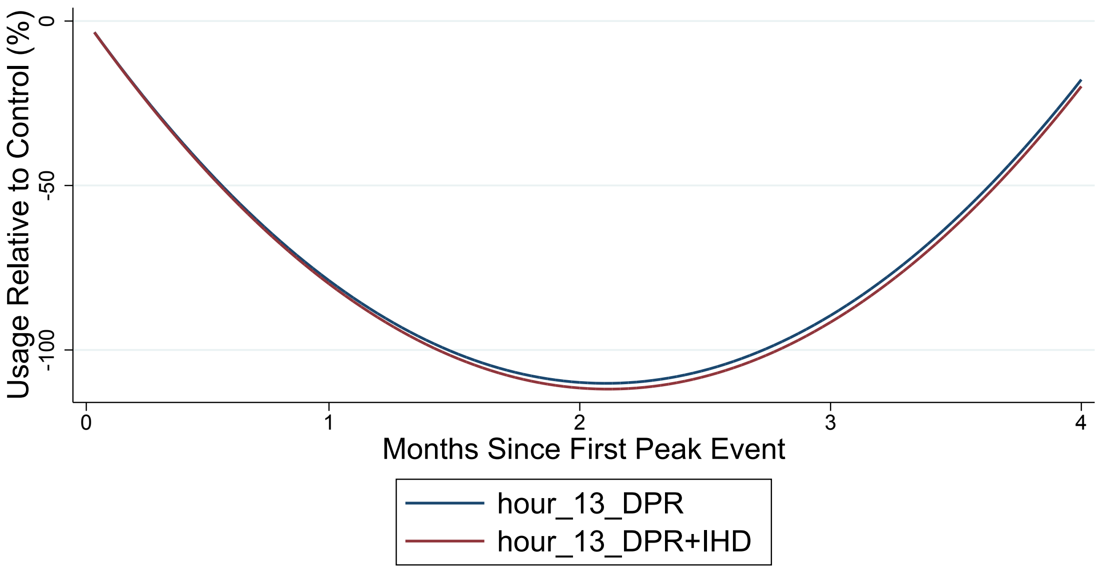

Figure B.93: DPR2 Quadratic Trend for Hour 1300

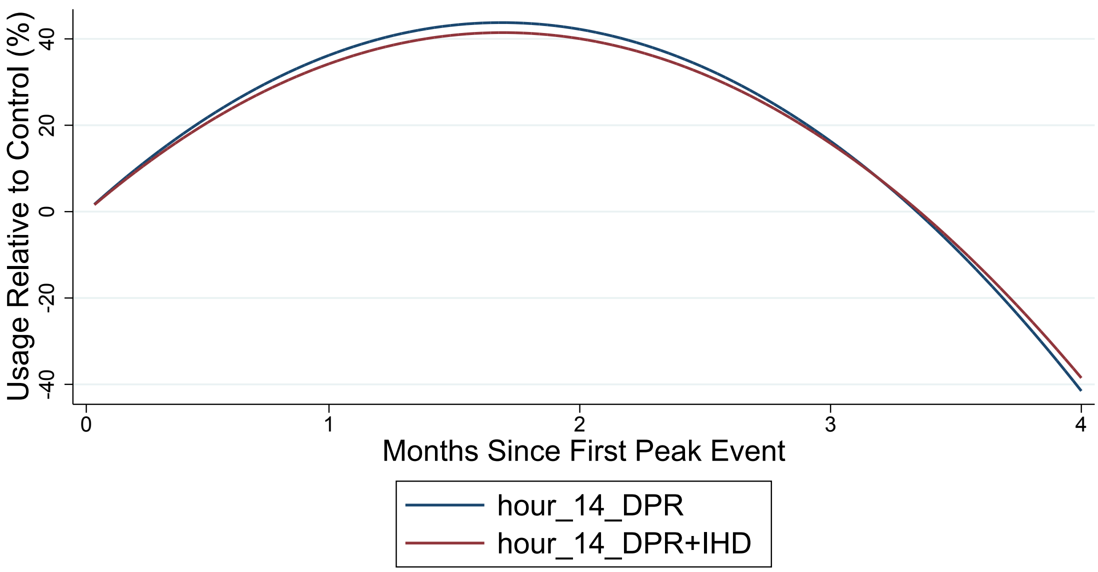

Figure B.94: DPR2 Quadratic Trend for Hour 1400

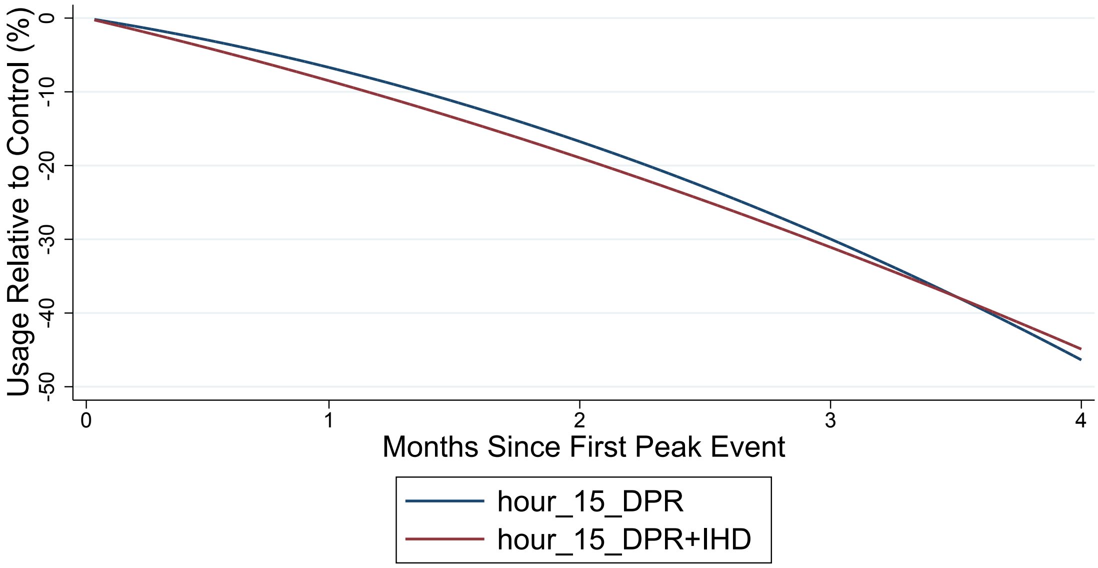

Figure B.95: DPR2 Quadratic Trend for Hour 1500

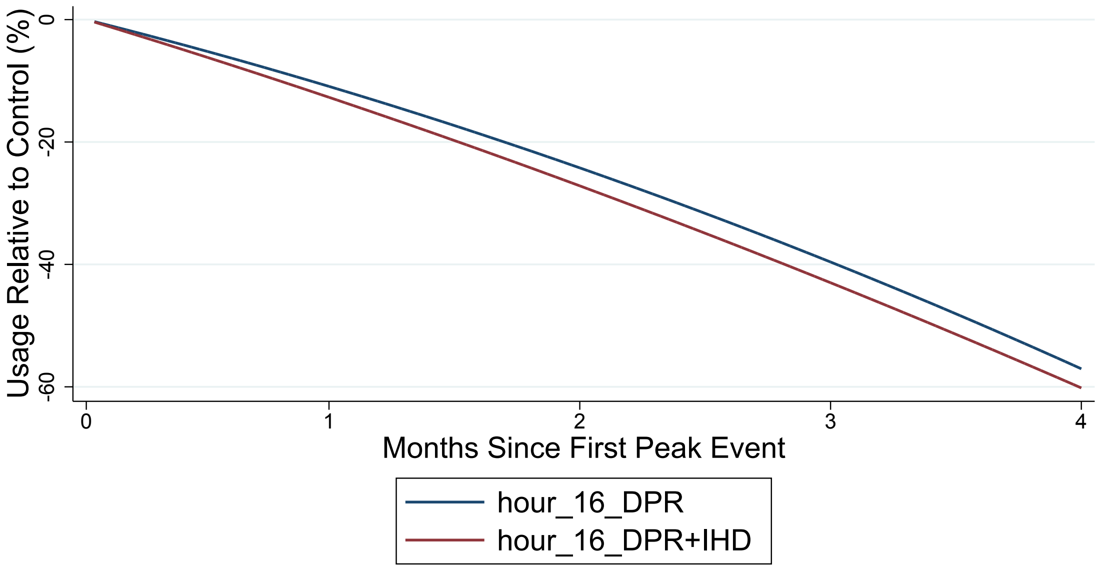

Figure B.96: DPR2 Quadratic Trend for Hour 1600

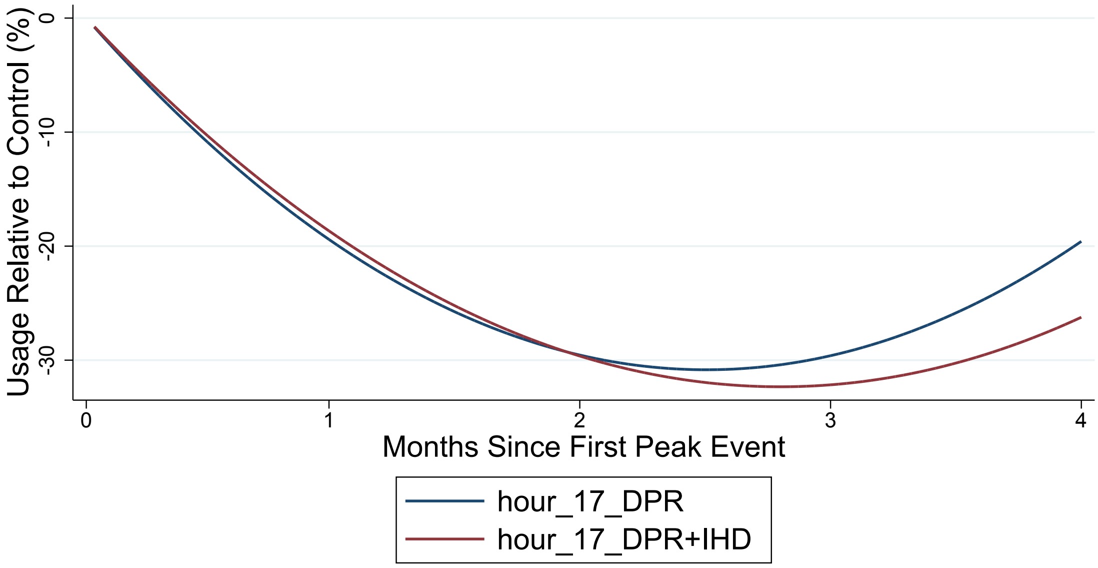

Figure B.97: DPR2 Quadratic Trend for Hour 1700

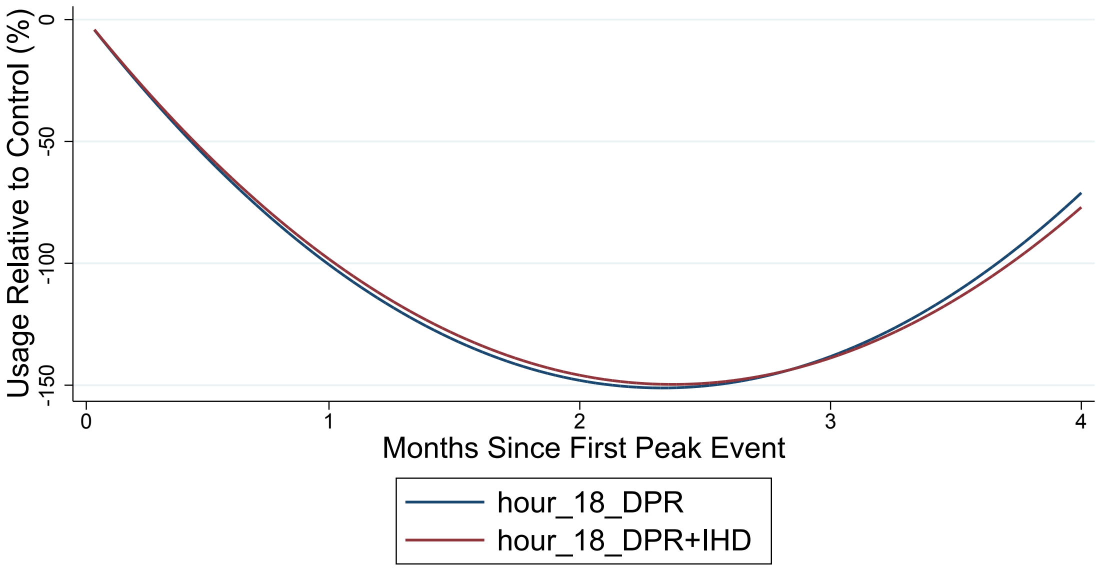

Figure B.98: DPR2 Quadratic Trend for Hour 1800

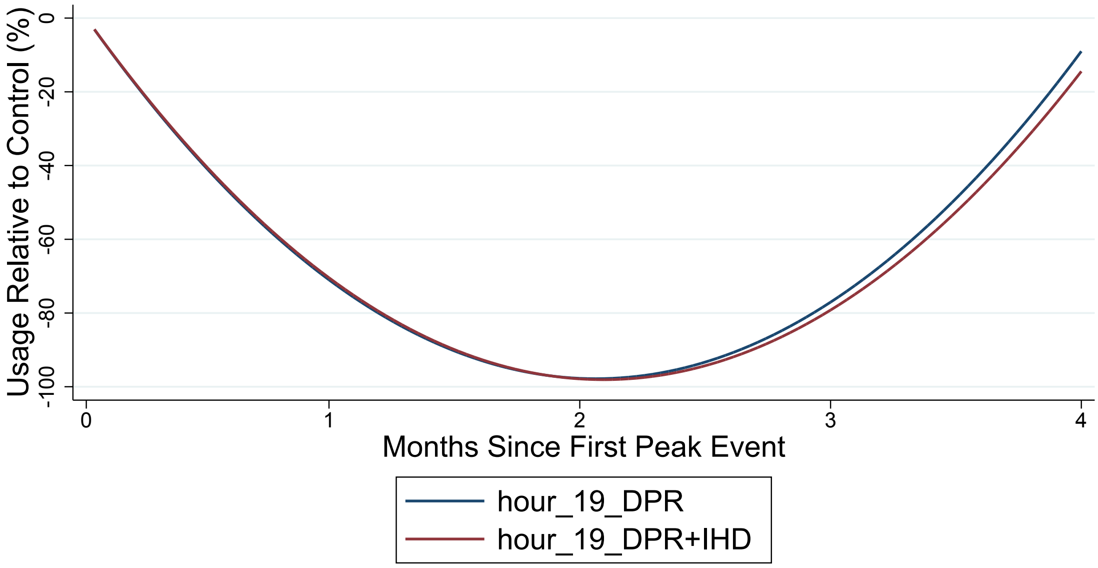

Figure B.99: DPR2 Quadratic Trend for Hour 1900

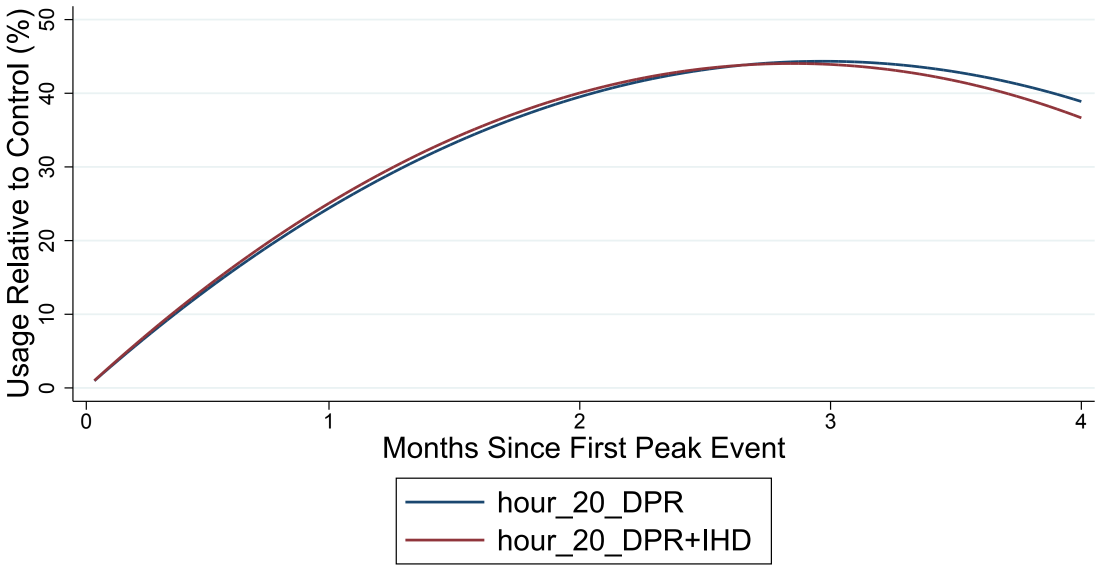

Figure B.100: DPR2 Quadratic Trend for Hour 2000

Table B.8: **DPP Habit Formation - 4 Months after 27/03/2013**

Variable	Trend Coefficient
trnd_hour_11_treatment_1	0.00164323***
	(0.00006466)
trnd_hour_12_treatment_1	0.00153256***
	(0.00006370)
trnd_hour_13_treatment_1	0.00171835***
	(0.00006349)
trnd_hour_14_treatment_1	0.00150019***
	(0.00006223)
trnd_hour_15_treatment_1	0.00129680***
	(0.00006103)
trnd_hour_16_treatment_1	0.00113667***
	(0.00006108)
trnd_hour_17_treatment_1	0.00110198***
	(0.00006250)
trnd_hour_18_treatment_1	0.00136466***
	(0.00006575)
trnd_hour_19_treatment_1	0.00068149***
	(0.00006545)
trnd_hour_20_treatment_1	0.00014419*
	(0.00006338)
trnd_hour_11_treatment_2	0.00251467***
	(0.00008010)
trnd_hour_12_treatment_2	0.00237033***
	(0.00007764)
trnd_hour_13_treatment_2	0.00235983***
	(0.00007599)
trnd_hour_14_treatment_2	0.00235726***
	(0.00007530)
trnd_hour_15_treatment_2	0.00213261***
	(0.00007359)
trnd_hour_16_treatment_2	0.00181320***
	(0.00007409)
trnd_hour_17_treatment_2	0.00187502***
	(0.00007704)
trnd_hour_18_treatment_2	0.00227460***
	(0.00008207)

trnd_hour_19_treatment_2	0.00195472***
	(0.00008356)
trnd_hour_20_treatment_2	0.00150640***
	(0.00008057)
trnd_hour_11_treatment_3	0.00172215***
	(0.00010878)
trnd_hour_12_treatment_3	0.00201904***
	(0.00010620)
trnd_hour_13_treatment_3	0.00214330***
	(0.00010702)
trnd_hour_14_treatment_3	0.00177208***
	(0.00010375)
trnd_hour_15_treatment_3	0.00138036***
	(0.00010203)
trnd_hour_16_treatment_3	0.00120800***
	(0.00010684)
trnd_hour_17_treatment_3	0.00092875***
	(0.00010681)
trnd_hour_18_treatment_3	0.00117125***
	(0.00011359)
trnd_hour_19_treatment_3	0.00157477***
	(0.00011713)
trnd_hour_20_treatment_3	0.00074948***
	(0.00011134)
trnd_hour_11_treatment_4	0.00418238***
	(0.00006717)
trnd_hour_12_treatment_4	0.00389552***
	(0.00006575)
trnd_hour_13_treatment_4	0.00393925***
	(0.00006565)
trnd_hour_14_treatment_4	0.00405826***
	(0.00006554)
trnd_hour_15_treatment_4	0.00395715***
	(0.00006444)
trnd_hour_16_treatment_4	0.00376794***
	(0.00006454)
trnd_hour_17_treatment_4	0.00386711***
	(0.00006622)
trnd_hour_18_treatment_4	0.00402781***

	(0.00006904)
trnd_hour_19_treatment_4	0.00355501***
	(0.00007037)
trnd_hour_20_treatment_4	0.00288667***
	(0.00006914)
Adjusted R^2	0.50069872
AIC	38432564
BIC	38433142
Number of obs. (mill)	14

Notes: The dependent variable is $ln(kWh)$ in 30-minute intervals. This specification included time and household fixed effects. Standard errors in brackets are clustered at the household level.
***Significant at the 1% level
**Significant at the 5% level
*Significant at the 10% level

Table B.9: DPR Habit Formation - 4 Months after 27/03/2013

Variable	Trend Coefficient
trnd_hour_11_treatment_5	0.00035049***
	(0.00005130)
trnd_hour_12_treatment_5	0.00013441**
	(0.00005018)
trnd_hour_13_treatment_5	0.00021114***
	(0.00004950)
trnd_hour_14_treatment_5	0.00018806***
	(0.00004844)
trnd_hour_15_treatment_5	0.00013809**
	(0.00004742)
trnd_hour_16_treatment_5	0.00004870
	(0.00004727)
trnd_hour_17_treatment_5	0.00026468***
	(0.00004840)
trnd_hour_18_treatment_5	0.00054788***
	(0.00005113)
trnd_hour_19_treatment_5	0.00056483***
	(0.00005203)
trnd_hour_20_treatment_5	0.00041381***
	(0.00005067)

trnd_hour_11_treatment_6	0.00023316***
	(0.00005156)
trnd_hour_12_treatment_6	0.00021380***
	(0.00005080)
trnd_hour_13_treatment_6	0.00023685***
	(0.00005039)
trnd_hour_14_treatment_6	0.00009782*
	(0.00004926)
trnd_hour_15_treatment_6	0.00016032***
	(0.00004863)
trnd_hour_16_treatment_6	0.00017236***
	(0.00004780)
trnd_hour_17_treatment_6	0.00027631***
	(0.00004878)
trnd_hour_18_treatment_6	0.00056376***
	(0.00005194)
trnd_hour_19_treatment_6	0.00036736***
	(0.00005331)
trnd_hour_20_treatment_6	0.00006431
	(0.00005135)
Adjusted R^2	0.48753011
AIC	36731851
BIC	36732139
Number of obs. (mill)	13

Notes: The dependent variable is $ln(kWh)$ in 30-minute intervals. This specification included time and household fixed effects. Standard errors in brackets are clustered at the household level.
***Significant at the 1% level
**Significant at the 5% level
*Significant at the 10% level

Table B.10: DPR Habit Formation - 4 Months after 17/08/2013

Variable	Trend Coefficient
trnd_hour_11_treatment_5	-0.00636126**
	(0.00199363)
trnd_hour_12_treatment_5	-0.00423685*
	(0.00199872)

trnd_hour_13_treatment_5	-0.00010305
	(0.00211058)
trnd_hour_14_treatment_5	-0.00376206
	(0.00223071)
trnd_hour_15_treatment_5	-0.00354276*
	(0.00166655)
trnd_hour_16_treatment_5	-0.00446603*
	(0.00176291)
trnd_hour_17_treatment_5	-0.00137808
	(0.00216900)
trnd_hour_18_treatment_5	-0.00458967*
	(0.00216682)
trnd_hour_19_treatment_5	0.00035869
	(0.00188883)
trnd_hour_20_treatment_5	0.00299457
	(0.00165397)
trnd_hour_11_treatment_6	-0.00665674***
	(0.00199290)
trnd_hour_12_treatment_6	-0.00430858*
	(0.00199740)
trnd_hour_13_treatment_6	-0.00036321
	(0.00210996)
trnd_hour_14_treatment_6	-0.00400523
	(0.00222983)
trnd_hour_15_treatment_6	-0.00381320*
	(0.00166550)
trnd_hour_16_treatment_6	-0.00490667**
	(0.00176174)
trnd_hour_17_treatment_6	-0.00150167
	(0.00216829)
trnd_hour_18_treatment_6	-0.00441056*
	(0.00216650)
trnd_hour_19_treatment_6	0.00024807
	(0.00188857)
trnd_hour_20_treatment_6	0.00302291
	(0.00165328)
Adjusted R^2	0.52120161
AIC	9727602
BIC	9727866

Number of obs. (mill)	40

Notes: The dependent variable is $ln(kWh)$ in 30-minute intervals. This specification included time and household fixed effects. Standard errors in brackets are clustered at the household level.
***Significant at the 1% level
**Significant at the 5% level
*Significant at the 10% level

Appendix C

Additional Attrition Analysis

Table C.1: Attrition Analysis - DPP

	Optout Analysis - LPM	Optout Analysis - Logit
	optout_analysis_1	optout_analysis_logit_1
hhold_inc_group==HI	0.038	0.157
	(0.064)	(0.260)
hhold_inc_group==LOW	0.076	0.290
	(0.054)	(0.204)
gas_usage_group==HI	-0.118	-0.427
	(0.090)	(0.349)
gas_usage_group==LOW	0.022	0.078
	(0.062)	(0.232)
elec_use_group==HI	-0.044	-0.237
	(0.057)	(0.242)
elec_use_group==LOW	0.113*	0.414*
	(0.047)	(0.181)
dwelling_type==NotUnit	-0.006	-0.006
	(0.059)	(0.214)
lga==AUBURN	0.001	0.321
	(0.205)	(0.548)
lga==BANKSTOWN	0.000	0.332
	(.)	(0.769)
lga==BURWOOD	0.000	0.000
	(.)	(.)
lga==CANADA BAY	-0.105	0.000
	(0.291)	(.)
lga==CESSNOCK	0.002	0.003
	(0.154)	(0.607)
lga==CONCORD	0.000	0.000
	(.)	(.)

lga==HORNSBY	-0.202	0.000
	(0.244)	(.)
lga==HURSTVILLE	-0.093	0.000
	(0.196)	(.)
lga==KOGARAH	-0.202	0.000
	(0.401)	(.)
lga==KU-RING-GAI	0.161	0.626
	(0.137)	(0.542)
lga==LAKE MACQUARIE	0.031	0.166
	(0.107)	(0.423)
lga==MOSMAN	0.000	0.000
	(.)	(.)
lga==MUSWELLBROOK	0.000	0.000
	(.)	(.)
lga==NEWCASTLE	0.041	0.193
	(0.110)	(0.433)
lga==OUT-OF-AREA	-0.089	0.000
	(0.402)	(.)
lga==RANDWICK	0.054	0.247
	(0.109)	(0.436)
lga==ROCKDALE	-0.240	0.000
	(0.243)	(.)
lga==SCONE	0.000	0.000
	(.)	(.)
lga==SOUTH SYDNEY	-0.010	-0.012
	(0.116)	(0.466)
lga==STRATHFIELD	0.000	0.000
	(.)	(.)
lga==SYDNEY	-0.124	0.000
	(0.299)	(.)
lga==WAVERLEY	0.000	0.000
	(.)	(.)
lga==WOOLLAHRA	0.313	0.953
	(0.292)	(0.947)
lga==WYONG	0.000	0.000
	(.)	(.)
climate_zone== 5.0000	-0.080	0.000
	(0.201)	(.)
_cons	0.154	-1.392**

	(0.196)	(0.518)
Adjusted R^2	-0.000	
Pseudo R^2		0.049
Number of Obs.	414.000	397.000

Table C.2: Attrition Analysis - DPP+Portal

	Optout Analysis - LPM	Optout Analysis - Logit
	optout_analysis_2	optout_analysis_logit_2
hhold_inc_group==HI	-0.115	-0.530
	(0.088)	(0.375)
hhold_inc_group==LOW	0.051	0.184
	(0.057)	(0.210)
gas_usage_group==HI	-0.063	-0.255
	(0.144)	(0.620)
gas_usage_group==LOW	-0.055	-0.218
	(0.063)	(0.236)
elec_use_group==HI	-0.014	-0.039
	(0.060)	(0.223)
elec_use_group==LOW	-0.065	-0.238
	(0.053)	(0.200)
dwelling_type==NotUnit	-0.012	-0.047
	(0.087)	(0.354)
lga==AUBURN	0.127	3.586
	(0.432)	(196.245)
lga==BANKSTOWN	0.162	3.729
	(0.404)	(196.244)
lga==BURWOOD	-0.069	0.000
	(0.297)	(.)
lga==CANADA BAY	0.040	0.000
	(0.421)	(.)
lga==CESSNOCK	0.025	0.137
	(0.145)	(0.572)
lga==CONCORD	0.000	0.000
	(.)	(.)
lga==HORNSBY	0.000	0.000
	(.)	(.)
lga==HURSTVILLE	-0.089	0.000
	(0.202)	(.)
lga==KOGARAH	0.000	0.000
	(.)	(.)
lga==KU-RING-GAI	0.295	1.216
	(0.177)	(0.745)
lga==LAKE MACQUARIE	0.085	0.361

	(0.108)	(0.441)
lga==MOSMAN	0.000	0.000
	(.)	(.)
lga==MUSWELLBROOK	0.129	0.000
	(0.566)	(.)
lga==NEWCASTLE	0.055	0.254
	(0.110)	(0.449)
lga==OUT-OF-AREA	0.000	0.000
	(.)	(.)
lga==RANDWICK	0.102	0.463
	(0.180)	(0.756)
lga==ROCKDALE	-0.063	0.000
	(0.406)	(.)
lga==SCONE	0.000	0.000
	(.)	(.)
lga==SOUTH SYDNEY	0.944***	0.000
	(0.229)	(.)
lga==STRATHFIELD	0.000	0.000
	(.)	(.)
lga==SYDNEY	-0.099	0.000
	(0.304)	(.)
lga==WAVERLEY	-0.128	0.000
	(0.406)	(.)
lga==WOOLLAHRA	0.158	0.679
	(0.166)	(0.685)
lga==WYONG	0.000	0.000
	(.)	(.)
climate_zone== 5.0000	0.128	3.559
	(0.406)	(196.245)
_cons	0.067	-4.467
	(0.408)	(196.245)
Adjusted R^2	0.020	
Pseudo R^2		0.036
Number of Obs.	338.000	321.000

Table C.3: **Attrition Analysis - DPP+Portal+Plug**

	Optout Analysis - LPM	Optout Analysis - Logit
	optout_analysis_3	optout_analysis_logit_3
hhold_inc_group==HI	0.150	0.806
	(0.143)	(0.611)
hhold_inc_group==LOW	0.060	0.176
	(0.096)	(0.368)
gas_usage_group==HI	-0.030	-0.192
	(0.145)	(0.533)
gas_usage_group==LOW	0.036	0.195
	(0.095)	(0.373)
elec_use_group==HI	-0.029	-0.069
	(0.099)	(0.414)
elec_use_group==LOW	0.061	0.331
	(0.087)	(0.369)
dwelling_type==NotUnit	0.261	0.000
	(0.239)	(.)
lga==AUBURN	-0.024	0.000
	(0.574)	(.)
lga==BANKSTOWN	0.000	0.000
	(.)	(.)
lga==BURWOOD	0.000	0.000
	(.)	(.)
lga==CANADA BAY	0.000	0.000
	(.)	(.)
lga==CESSNOCK	-0.003	0.000
	(0.296)	(.)
lga==CONCORD	0.000	0.000
	(.)	(.)
lga==HORNSBY	-0.089	0.000
	(0.357)	(.)
lga==HURSTVILLE	0.030	0.000
	(0.334)	(.)
lga==KOGARAH	0.000	0.000
	(.)	(.)
lga==KU-RING-GAI	0.175	4.551
	(0.251)	(201.401)
lga==LAKE MACQUARIE	0.252	4.952

	(0.216)	(201.401)
lga==MOSMAN	0.000	0.000
	(.)	(.)
lga==MUSWELLBROOK	0.000	0.000
	(.)	(.)
lga==NEWCASTLE	0.222	4.848
	(0.215)	(201.401)
lga==OUT-OF-AREA	-0.000	0.000
	(0.431)	(.)
lga==RANDWICK	-0.032	3.372
	(0.234)	(201.400)
lga==ROCKDALE	-0.000	0.000
	(0.335)	(.)
lga==SCONE	0.000	0.000
	(.)	(.)
lga==SOUTH SYDNEY	-0.057	0.000
	(0.343)	(.)
lga==STRATHFIELD	0.000	0.000
	(.)	(.)
lga==SYDNEY	0.000	0.000
	(.)	(.)
lga==WAVERLEY	0.000	0.000
	(.)	(.)
lga==WOOLLAHRA	0.000	0.000
	(.)	(.)
lga==WYONG	0.000	0.000
	(.)	(.)
climate_zone== 5.0000	-0.090	0.000
	(0.434)	(.)
_cons	-0.268	-6.079
	(0.473)	(201.402)
Adjusted R^2	-0.071	
Pseudo R^2		0.065
Number of Obs.	142.000	124.000

Table C.4: **Attrition Analysis - DPP+IHD**

	Optout Analysis - LPM	Optout Analysis - Logit
	optout_analysis_4	optout_analysis_logit_4
hhold_inc_group==HI	-0.021	-0.144
	(0.036)	(0.197)
hhold_inc_group==LOW	0.044	0.189
	(0.029)	(0.139)
gas_usage_group==HI	-0.031	-0.156
	(0.071)	(0.372)
gas_usage_group==LOW	-0.060	-0.261
	(0.033)	(0.157)
elec_use_group==HI	0.014	0.075
	(0.029)	(0.144)
elec_use_group==LOW	0.002	-0.003
	(0.025)	(0.125)
dwelling_type==NotUnit	-0.126***	-0.511**
	(0.037)	(0.167)
lga==AUBURN	-0.146	-0.599
	(0.162)	(0.672)
lga==BANKSTOWN	-0.255	-1.284
	(0.141)	(0.680)
lga==BURWOOD	-0.030	-0.081
	(0.133)	(0.617)
lga==CANADA BAY	-0.150	0.000
	(0.240)	(.)
lga==CESSNOCK	-0.050	-0.201
	(0.060)	(0.267)
lga==CONCORD	-0.151	0.000
	(0.336)	(.)
lga==HORNSBY	-0.140*	-1.001*
	(0.067)	(0.467)
lga==HURSTVILLE	-0.176	0.000
	(0.125)	(.)
lga==KOGARAH	-0.174	0.000
	(0.155)	(.)
lga==KU-RING-GAI	-0.089	-0.292
	(0.088)	(0.443)
lga==LAKE MACQUARIE	-0.067	-0.257

	(0.049)	(0.221)
lga==MOSMAN	0.000	0.000
	(.)	(.)
lga==MUSWELLBROOK	0.136	0.451
	(0.198)	(0.783)
lga==NEWCASTLE	-0.127*	-0.528*
	(0.051)	(0.233)
lga==OUT-OF-AREA	-0.173	0.000
	(0.335)	(.)
lga==RANDWICK	-0.090	-0.345
	(0.075)	(0.384)
lga==ROCKDALE	-0.107	-0.508
	(0.096)	(0.535)
lga==SCONE	0.000	0.000
	(.)	(.)
lga==SOUTH SYDNEY	-0.199*	0.000
	(0.099)	(.)
lga==STRATHFIELD	-0.210	0.000
	(0.142)	(.)
lga==SYDNEY	0.236	0.610
	(0.239)	(0.930)
lga==WAVERLEY	-0.124	-0.547
	(0.067)	(0.342)
lga==WOOLLAHRA	-0.007	0.032
	(0.078)	(0.353)
lga==WYONG	-0.170	0.000
	(0.335)	(.)
climate_zone== 5.0000	-0.109	-0.405
	(0.133)	(0.539)
_cons	0.465***	0.182
	(0.135)	(0.555)
Adjusted R^2	0.028	
Pseudo R^2		0.062
Number of Obs.	1048.000	1009.000

Table C.5: Attrition Analysis - DPR

	Optout Analysis - LPM	Optout Analysis - Logit
	optout_analysis_5	optout_analysis_logit_5
hhold_inc_group==HI	0.003	-0.001
	(0.029)	(0.264)
hhold_inc_group==LOW	0.014	0.078
	(0.023)	(0.210)
gas_usage_group==HI	0.020	0.182
	(0.034)	(0.297)
gas_usage_group==LOW	-0.035	-0.309
	(0.024)	(0.221)
elec_use_group==HI	-0.014	-0.191
	(0.026)	(0.264)
elec_use_group==LOW	-0.004	-0.060
	(0.021)	(0.191)
dwelling_type==NotUnit	-0.017	-0.172
	(0.025)	(0.232)
lga==AUBURN	0.023	0.412
	(0.052)	(0.545)
lga==BANKSTOWN	0.000	0.000
	(.)	(.)
lga==BURWOOD	0.000	0.000
	(.)	(.)
lga==CANADA BAY	0.000	0.000
	(.)	(.)
lga==CESSNOCK	0.000	0.333
	(.)	(0.760)
lga==CONCORD	0.000	0.000
	(.)	(.)
lga==HORNSBY	0.000	0.000
	(.)	(.)
lga==HURSTVILLE	0.000	0.000
	(.)	(.)
lga==KOGARAH	0.000	0.000
	(.)	(.)
lga==KU-RING-GAI	-0.044	-0.290
	(0.068)	(0.608)
lga==LAKE MACQUARIE	0.043	0.717

	(0.057)	(0.606)
lga==MOSMAN	0.000	0.000
	(.)	(.)
lga==MUSWELLBROOK	0.000	0.000
	(.)	(.)
lga==NEWCASTLE	0.043	0.683
	(0.054)	(0.587)
lga==OUT-OF-AREA	0.000	0.000
	(.)	(.)
lga==RANDWICK	0.000	0.000
	(.)	(.)
lga==ROCKDALE	0.000	0.000
	(.)	(.)
lga==SCONE	0.164*	1.346
	(0.067)	(0.696)
lga==SOUTH SYDNEY	0.009	0.378
	(0.062)	(0.575)
lga==STRATHFIELD	0.000	0.000
	(.)	(.)
lga==SYDNEY	-0.035	0.000
	(0.079)	(.)
lga==WAVERLEY	0.000	0.000
	(.)	(.)
lga==WOOLLAHRA	0.000	0.000
	(.)	(.)
lga==WYONG	0.000	0.000
	(.)	(.)
climate_zone== 5.0000	0.009	0.000
	(0.069)	(.)
_cons	0.048	-1.858**
	(0.058)	(0.582)
Adjusted R^2	0.002	
Pseudo R^2		0.049
Number of Obs.	681.000	648.000

Table C.6: **Attrition Analysis - DPR+IHD**

	Optout Analysis - LPM	Optout Analysis - Logit
	optout_analysis_6	optout_analysis_logit_6
hhold_inc_group==HI	0.004	0.022
	(0.034)	(0.307)
hhold_inc_group==LOW	0.025	0.245
	(0.026)	(0.213)
gas_usage_group==HI	0.032	0.250
	(0.036)	(0.256)
gas_usage_group==LOW	-0.020	-0.192
	(0.027)	(0.232)
elec_use_group==HI	-0.021	-0.198
	(0.029)	(0.263)
elec_use_group==LOW	0.044	0.359
	(0.025)	(0.191)
dwelling_type==NotUnit	-0.048	-0.289
	(0.030)	(0.205)
lga==AUBURN	0.054	-0.234
	(0.087)	(0.391)
lga==BANKSTOWN	0.000	0.000
	(.)	(.)
lga==BURWOOD	0.000	0.000
	(.)	(.)
lga==CANADA BAY	0.000	0.000
	(.)	(.)
lga==CESSNOCK	0.000	-0.078
	(.)	(0.634)
lga==CONCORD	0.000	0.000
	(.)	(.)
lga==HORNSBY	0.000	0.000
	(.)	(.)
lga==HURSTVILLE	0.000	0.000
	(.)	(.)
lga==KOGARAH	0.000	0.000
	(.)	(.)
lga==KU-RING-GAI	0.035	0.194
	(0.075)	(0.417)
lga==LAKE MACQUARIE	0.007	-0.057

	(0.064)	(0.420)
lga==MOSMAN	0.000	0.000
	(.)	(.)
lga==MUSWELLBROOK	0.109	0.190
	(0.089)	(0.531)
lga==NEWCASTLE	-0.008	-0.149
	(0.065)	(0.424)
lga==OUT-OF-AREA	0.000	0.000
	(.)	(.)
lga==RANDWICK	0.000	0.000
	(.)	(.)
lga==ROCKDALE	0.000	0.000
	(.)	(.)
lga==SCONE	0.000	0.000
	(.)	(.)
lga==SOUTH SYDNEY	-0.066	-0.567
	(0.074)	(0.442)
lga==STRATHFIELD	0.000	0.000
	(.)	(.)
lga==SYDNEY	0.031	0.000
	(0.087)	(.)
lga==WAVERLEY	0.000	0.000
	(.)	(.)
lga==WOOLLAHRA	0.000	0.000
	(.)	(.)
lga==WYONG	0.000	0.000
	(.)	(.)
climate_zone== 5.0000	0.082	0.000
	(0.102)	(.)
_cons	-0.004	-1.508***
	(0.090)	(0.413)
Adjusted R^2	0.017	
Pseudo R^2		0.074
Number of Obs.	660.000	649.000

Bibliography

AEFI (2014). Smart Grid, Smart City: Shaping Australia's energy future national cost benefit assessment. Report p-ALL.

Allcott, H. (2011). Rethinking real-time electricity pricing. *Resource and Energy Economics 33*, 820–842.

Atkinson, S. (1979). Responsiveness to time-of-day electricity pricing: first emprical results. *Journal of Econometrics 9*, 79–95.

Ausgrid (2014). SGSC customer applications technical compendium. Report p-ALL.

Boiteux, M. (1960). Peak-load pricing. *Journal of Business 28*, 157–179.

Caves, D. and J. Christensen, L.R. Herriges (1984). Consistency of residential customer response in time-of-use electricity pricing experiments. *Journal of Econometrics 26*, 179–203.

Caves, D. and L. Christensen (1980). Consistency of residential customer response in time-of-use electricity pricing experiments. *Journal of Econometrics 14*, 287–306.

Crew, M. A., C. Fernando, and P. Kleindorfer (1995). The theory of peak load pricing: a survey. *Journal of Regulatory Economics 8*, 215–248.

Farugui, A. and S. Sergici (2010). Household response to dynamic pricing of electricity: a survey of 15 experiments. *Regulatory Economics 38*, 193–225.

Faruqui, A. and S. Sergici (2011). Dynamic pricing of electricity in the mid-atlantic region: econometric results from the baltimore gas and electricity company experiment. *Journal of Regulatory Economics 40*, 82–109.

Frontier Economics (2014). Smart Grid, Smart City: Customer applications trials: Data analysis methodology report. Report p-ALL, Frontier Economics.

Futura Consulting (August 2011). Smart Grid, Smart City: Detailed sampling design. Report.

Herriges, J., D. Caves, and L. Christensen (1984). Modeling alternative residential peak-load electricity rate structures. *Journal of Econometrics 26*, 249–268.

Herter, K. (2007). Residential implementation of critical-peak pricing of electricity. *Energy Policy 35*, 2121–2130.

Herter, K., P. McAuliffe, and A. Rosenfeld (2007). An exploratory analysis of California residential customer response to critical peak pricing of electricity. *Energy 32*, 25–34.

Herter, K. and S. Wayland (2010). Residential response to critical-peak pricing of electricity: California evidence. *Energy 35*, 1561–1567.

Ida, T., K. Ito, and M. Tanaka (2013). Using dynamic electricity pricing to address energy cirses evidence from randomized field experiments. *American Economic Review: Papers & Proceedings 101*, 83–87.

Jessoe, K. and D. Rapson (2014). Knowledge is (less) power: Experimental evidence from residential energy use. *American Economic Review 104*, 1417–1438.

Jetlun (`http://www.jetlun.com/am.html`). Appliance module. Accessed: 03/03/2016.

Joskow, P. L. and C. D. Wolfram (2012). Dynamic pricing of electricity. *American Economic Review 102*, 381–385.

Kahn, A. E. (1970). *The Economics of Regulation: Principles and Institutions*, Volume 1. John Wiley & Sons.

Kiesling, L. (2008). Digital technology, demand response, and customer choice: Efficiency benefits. In *NARUC Winter Meetings*, Washington, DC. 18 February 2008.

RLW Analytics (2004). AmerenUE residential TOU pilot study load research analysis: First look results. Report p-ALL.

Rocky Mountain Institute (2006). Automated demand response system pilot: Final report. Report p-ALL, Snowmass, CO.

Wolak, F. A. (2006). Residential customer response to real-time pricing: The Anaheim critical-peak pricing experiment. Centre for the Study of Energy Markets Working Paper Series.

Wolak, F. A. (2011). Do residential customers respond to hourly prices? evidence from a dynamic pricing experiment. *American Economic Review: Papers & Proceedings 101*, 83–87.