Jinmahn Jo (ID#: 915528897)

Contents

List of Tables

List of Figures

1 Introduction

These days many utilities are moving towards Time-of-Use (TOU) electricity tariff structures that raise the rate for peak demand hours to the predetermined level, which does not vary across days. Many evaluations of experiments that assess how residential consumers respond to TOU rates consistently document reductions in electricity consumption during peak hours. However, those studies do not examine how the reductions in household electricity consumption are being achieved. In this research project, I decompose the demand reductions during the peak hours into two different sources of energy savings: 1) energy savings derived from the reduction in electricity consumption for temperature-control (e.g., cooling and heating), and 2) energy savings from non-temperature-control uses (e.g., lighting, operating appliances, and cooking).

My study examines 30-minute interval electricity consumption data from 4,096 Irish households that participated in a TOU pricing experiment conducted from July 2009 to December 2010 by the Commission for Energy Regulation (CER), the regulator for electricity and natural gas sectors in Ireland. In the region studied, heating accounts for a large portion of residential electricity consumption. Using Difference-in-Differences (DID) strategy, I estimate how savings obtained from the TOU program vary with the magnitude of the increase in price during the peak hours. In addition, I measure how savings alter with the daily temperature. By doing so, I can identify the share of energy savings during the peak hours stemming from the two distinct drivers of household electricity consumption (i.e., temperature-control and non-temperature-control uses). Overall, I find that deploying TOU prices reduces residential peak-hour demand for electricity by nearly 10%. Importantly, I also find that nearly half of the energy savings stem from reductions in electricity consumed for temperature-control use.

The findings provide new insights into the potential benefits of adopting even more dynamic price structures, e.g., Real-Time Pricing (RTP), which would vary the retail price not only across hours of the day but across days according to contemporaneous generating costs. Intuitively, if the energy savings caused by adopting TOU prices stemmed entirely from reductions in non-temperature-control-driven uses, then we would not expect the savings to vary meaningfully across days. In other words, the energy savings would be similar on days with mild temperatures and days with extreme temperatures, when the demand for electricity (and the cost of supplying it) peaks. However, my results illustrate that a sizable share of the energy savings caused by moving towards TOU tariffs does stem from reductions in the use of electricity for temperature-control use. Consequently, even though the TOU rates do not vary across days, the tariff structure already induces substantial reductions in electricity consumption on days in which the temperatures are extreme, in turn, the grid is most burdened. And this suggests that, at least currently, the additional gains from switching from TOU prices to RTPs may be smaller than many economists have thought.

To further examine the potential gains from switching from TOU to RTP regime, I utilize my estimate of the heterogeneity in electricity consumption reductions under the TOU experiment to predict the impact of adopting an RTP-like tariff structure. While my results imply that allowing the peak-hour prices to vary across days would induce moderately larger energy savings on days with more extreme temperatures, the magnitude of the increased savings on high-demand days would be fairly small. This prediction comes from the fact that the reductions in electricity consumption during the peak hours in the experiment are quite insensitive to the size of the peak-period price increase. Indeed, this is precisely the result discussed in Prest (2020). Importantly, my findings extend the previous work by highlighting that it is the temperature-control-driven energy savings that are insensitive to the magnitude of the price changes. And according to my empirical results, the reduction in electricity consumption for non-temperature-control uses is proportional to the size of the tariff change. So, the low responsiveness to the peak price variations in the paper seems reasonable because the energy savings from non-temperature-control uses only account for half of the total savings.

To sum, my results demonstrate that, by reducing household electricity consumption for temperature-control use, TOU prices are already effectively lowering the demand for electricity during the peak hours of the peak demand days. Moreover, I ultimately predict that moving from TOU towards RTP-like pricing would not significantly alter residential electricity consumption, especially during the peak demand hours of the days with extreme temperatures. An important policy implication of the empirical findings is that designing an incentive to make residential electricity consumption for temperature-control use more responsive to price variations could be a key to unlocking the full benefits that time-varying price structures could provide.

2 Data

2.1 Description of CER Experiment[1]

The Commission for Energy Regulation (CER), which is the regulator for the electricity and natural gas sectors in Ireland, conducted the Smart Metering Electricity Consumer Behavior Trial (hereafter, the "trial") between July 2009 and December 2010. As part of the Smart Metering Project initiated in 2007, the trial's purpose was to assess the impact of various TOU tariff structures, along with different Demand-Side Management (DSM) stimuli, on residential electricity consumption. The CER carefully recruited households to construct a representative sample of the national population. Opt-in to the trial was voluntary. Participants received balancing credits not to incur any extra costs than if they were on the regular electric tariff (i.e., the flat rate of 14.1 cents per kWh). Also, they received a thank-you payment of 25 cents after pre- and post-trial surveys. All credits were distributed outside the treatment period to avoid unintended effects on participants' electricity consumption.[2]

The households who voluntarily opt-in to the experiment were randomly assigned to control and treatment

[1] The detail about the CER experiment presented hereinbelow is a summary of Commission for Energy Regulation (2011).

[2] While the first balancing credit was paid at the end of the base period (i.e., in December 2009), the participants received the second one at the immediate month after the treatment period (i.e., in January 2011). And the after-survey payments were credited to their bill with the balancing credits.

groups.[3] Baseline electricity consumption data were collected during the second half of 2009 (i.e., July to December 2009), while the treatment period was from January through December 2010. All treated households received two kinds of treatments simultaneously: 1) one of four TOU tariff structures and 2) one of hour DSM stimuli. In other words, there were 16 distinct treatment subgroups. The CER provided the treated with a fridge magnet and stickers to facilitate accustoming them to the TOU pricing schemes.[4] On the contrary, the households allocated to the control group remained on the normal flat tariff.

The four TOU tariff structures had different prices during each of the three rate periods in a day. The day in the treatment period was divided into three periods: 1) peak rate period from 5:00 p.m to 7:00 p.m., 2) day rate period from 8:00 a.m. to 5:00 p.m. and from 7:00 p.m. to 11:00 p.m., and 3) night rate period 11:00 p.m. to 8:00 a.m. As illustrated in Figure 1, the order of magnitude in rate changes for the peak rate period is the opposite of that for the rest of the rate periods. The reason for designing the tariff structures in such a way is to enable participating households to face similar energy bills on average when maintaining their electricity consumption pattern, regardless of the rate structures to which they were assigned.

The four DSM stimuli differed in the degree or the frequency of feedback on each household's electricity usage information. The control group just received their bills at the same cycle (i.e., bi-monthly). On the contrary, all households assigned to the treatment group received a detailed energy usage statement combined with their bill, including their detailed weekly usage, average weekly costs, tips on reducing electricity use, and comparisons to peer households. The first stimulus subgroup received a bill with a detailed energy statement bi-monthly, while the second subgroup received the documents every month. An electricity monitor, which displays their usage against their pre-set daily budget, was also provided for the households allocated to the third DSM stimulus subgroup. The last stimulus subgroup received an Overall Load Reduction (OLR) incentive. Under the OLR incentive, the households that reached their 10% reduction target over the eight-month period beginning May 2010 were rewarded with 20 Euros.[5]

[3]The optimal sample size for the trial was determined to be 4,300 participants in the design phase. In the allocation phase, 5,028 households were assigned to the control and treatment groups to consider participant attrition. The published CER experiment data only include electricity consumption data only for 4,225 households.

[4]The fridge magnet and stickers outlined the timebands during which different prices were applied. Moreover, they were tailored for each tariff group.

[5]A household's reduction target in electricity consumption was set based on the participant's actual usage during the first four months of the treatment period. And the households in the last DSM stimulus subgroup were updated on their progress with each bi-monthly bill.

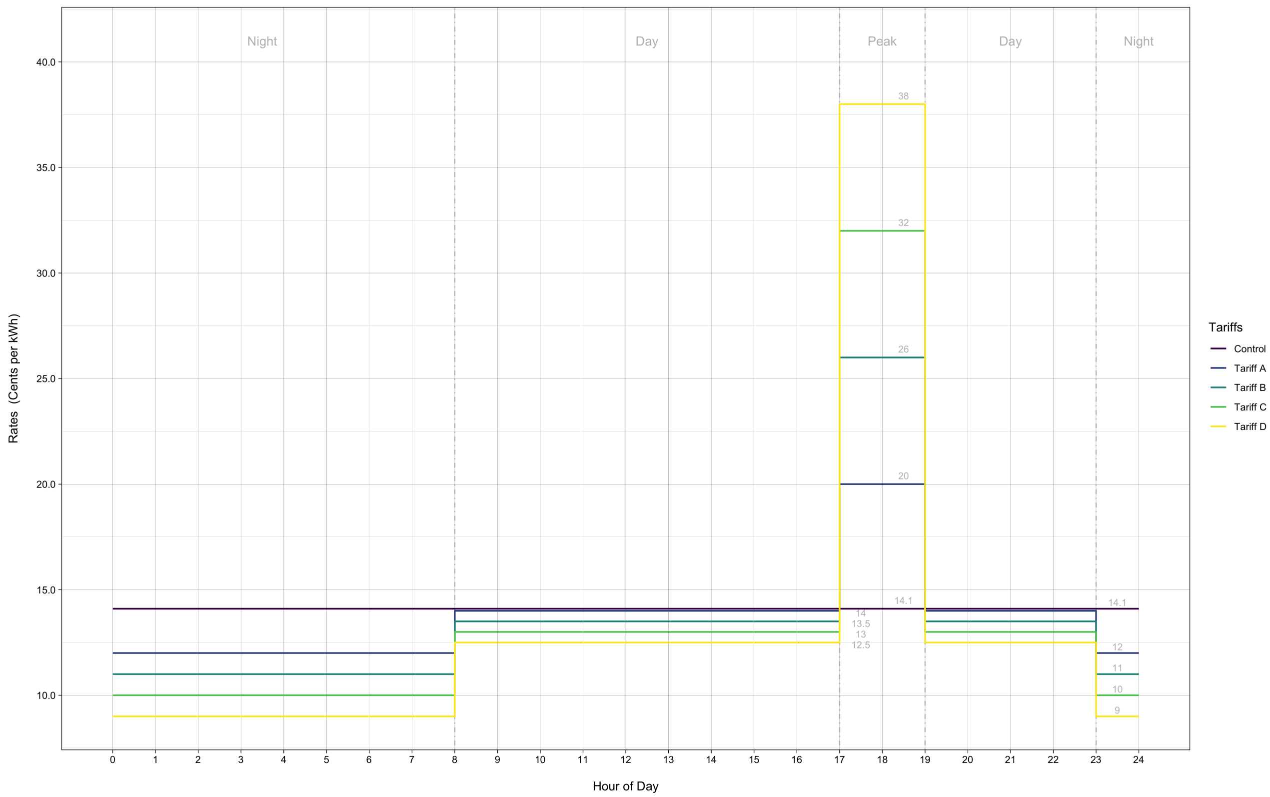

Figure 1: Time-Of-Use Pricing Structures

2.2 Description of CER Experiment Data

The CER experiment dataset disseminated by the Irish Social Science Data Archive (ISSDA) consists of participating households' electricity consumption and survey data.

Throughout the baseline and treatment periods, meter reads for residential participants were recorded in 30-minute intervals. The high granularity of the electricity consumption data generated from a well-designed experiment enables quantifying where the energy savings stem from when transferring to TOU electricity pricing for each of the three rate periods.

The survey data contains participants' responses to more than 300 questions in both pre- and post-trial surveys. The primary purpose of the two surveys was to gather trial-associated experiential and attitudinal feedback from the households. The surveys also included questions intended to collect residential participants' socio-demographic characteristics. In addition, questions about the physical attributes of their house were included in the surveys.

My empirical analysis throughout this paper uses the sample constructed by including observations only for non-holiday weekdays in the published electricity consumption data because the TOU rates were active just on those days.[6] This process results in 4,096 households.

The control and treatment groups in the sample are largely balanced, as shown in Table 2. Such indifferences between the two groups over many observables are consistent with previous studies that also examined the CER experiment dataset.[7]

Table 1: Treatment and Control Group Assignments

Table 2: Summary Statistics and Differences in Means for Treatment and Control Groups

Figure 2: Average Consumption by Hour of Day

2.3 Description of Weather Data

In this research, reliable weather data are an essential element. The main interest of the majority of TOU papers was to measure how residential consumers respond to TOU prices or the heterogeneity in the responsiveness of households across different information stimuli. Hence, those studies usually do not control for temperature variations directly. For example, Pon (2017) and Prest (2020), which also exploited the CER experiment dataset, added weak-of-sample and month-by-year fixed effects (FEs) to their specifications, respectively, in order to control for variations in usage due to seasonal changes. On the other hand, the primary objective of this paper is to decompose the TOU-price-inducing demand reductions during the peak hours into two parts–reductions in temperature-control use and those in non-temperature-control uses. Since the electricity consumption for temperature-control use is driven by weather, especially temperature, it is necessary to link the 30-minute interval consumption data and weather data with an appropriate level of resolution.

I utilize average daily temperatures to quantify the energy savings of each of the two different sources after introducing TOU prices. More granular temperatures, like hourly temperatures, are not a dominant determinant of electricity demand for temperature-control use at a point in time. It is not easy to believe that residential

[6]The sample is a panel data of households with reliable meter reads only. Specifically, the residential participants who had no consumption for eight days or more are excluded from the sample. In addition, I drop the meter reads for the days when several participating households' consumption data were missed.

Although I utilize the sample satisfying the following criteria too for the empirical analysis, applying the criteria does not change results: 1) Exclude the day immediately following the end of daylight-saving time due to noticeably different consumption levels in the same hours of the day; 2) Drop the observations for the last five days of the baseline and treatment periods because of extraordinarily high electricity demand on those days.

[7]To check the balance between the control and treatment groups, Prest (2020) employs a linear probability model, while a probit model is used in Pon (2017).

customers adjust their electricity consumption according to ever-changing outside temperatures elaborately and instantly. Furthermore, as shown in Figure 2, their electricity demand is the lowest in the early morning, the coldest time of the day. Considering those two points, I measure the TOU-tariff-inducing reductions in electricity consumption conditional on the average heating need in a given day.

I exploit hourly temperature data for the Dublin airport weather station, provided by Met Eireann, Ireland's National Meteorological Service, to compute average daily temperatures. There is no available location information in the published CER experiment data for privacy and security reasons. Therefore, it is not possible to match a participant's consumption data with weather data of the closest weather monitoring station to him. But fortunately, in Ireland, temperatures do not vary much across areas for a given day. As demonstrated in Table 3, the temperature correlations between the Dublin station and stations near densely populated cities are high. Because of this reason, I use the mean daily temperatures obtained by averaging the Dublin airport station's hourly temperatures as the representative temperatures in the following analysis.

Using the average daily temperatures, I calculate daily HDDs. Instead of 65 degrees of Fahrenheit ($^{\circ}F$), which is a normal base temperature in the United States, $60^{\circ}F$ is utilized to compute daily HDDs, according to Liu and Sweeney (2012). The upper part of Figure 7 shows that many days in the treatment period had lower average daily temperatures than the lowest one during the baseline period. The evolving pattern of heating-purpose demand for electricity on days with extreme–at least in Ireland–temperatures could be significantly different under distinct rate structures–flat rate and TOU rates. If this is true, the lack of counterfactual consumption observations will cause bias in the measured impact of introducing TOU rates on household electricity consumption. So, I drop observations for those days during the treatment period when constructing the sample to address the possibility.

Table 3: Correlations in Temperature for Major Cities in Ireland

Figure 3: Average Daily Temperature by Date

2.4 Empirical Strategy

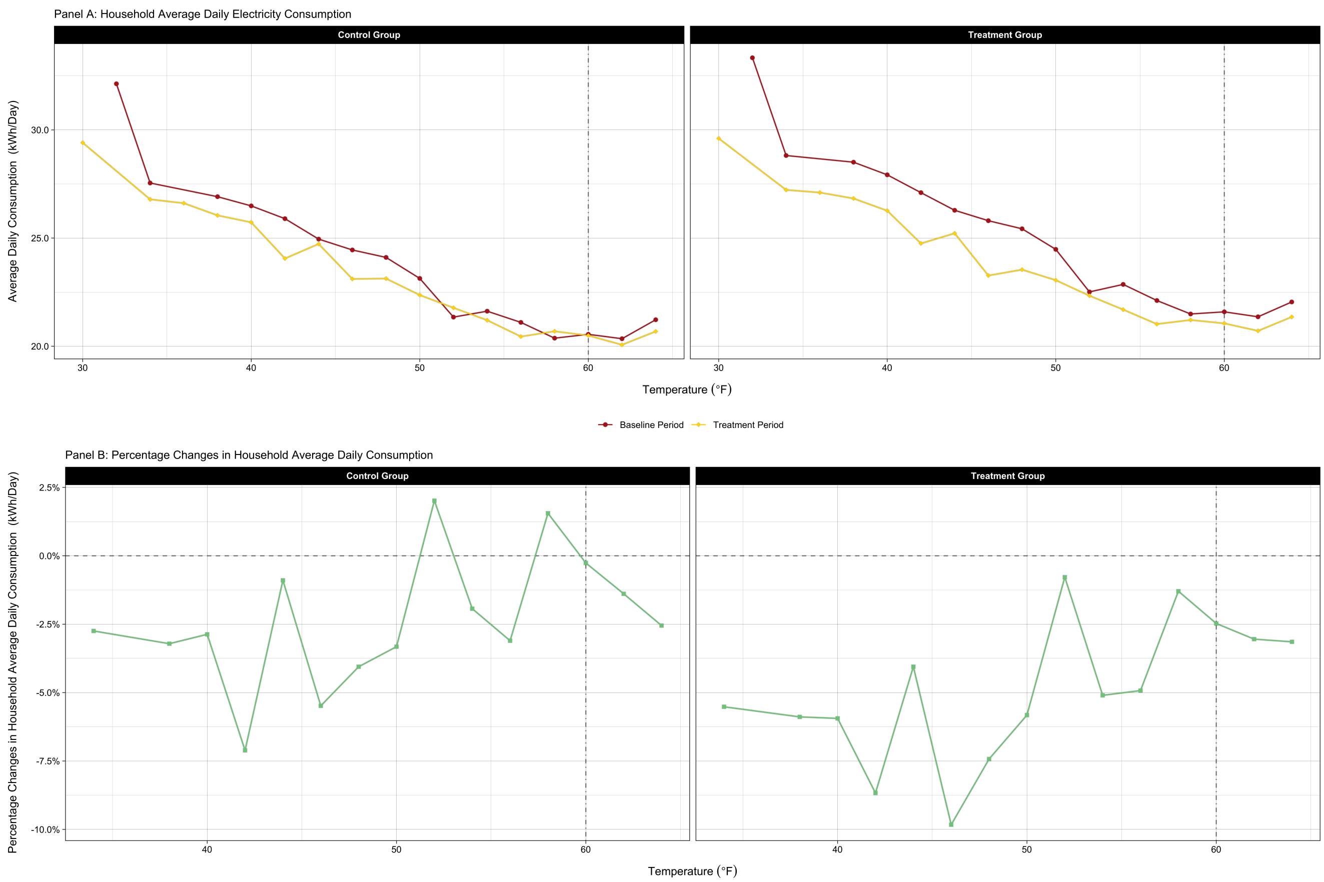

Figure 4: Pre- and Post-Treatment Household Average Daily Electricity Consumption

Figure 4, which shows household average daily electricity consumption over temperature and the pre and post differences in the consumption, clearly demonstrates the motivation of this research project.[8] As illustrated in Panel A of the figure, household demand for electricity grew as the temperature decreased. In other words, in addition to temperature-insensitive electricity demand (i.e., for non-temperature-control uses), there was a sizeable demand for electricity for heating (i.e., for temperature-control use) in Irish households, which is highly responsive to temperature variations. In this research, I determine not only how much consumption changes, on average, in response to the time-varying tariffs but also how their impact varies across days with different temperatures. In other words, the dynamic-pricing-causing effects on heating and non-heating electricity uses are separately estimated to figure out the primary source of energy savings. As shown in the figure, households in the control group also consumed less electricity during the treatment period, especially on days with low

[8] An important feature also stands out from the figure: the minimum household electricity consumption occurred at around $60^\circ F$. This phenomenon supports the setting of the reference temperature for calculating daily HDDs at the very level.

temperatures, although their percentage reduction is smaller than that of the treated households.[9] This suggests the necessity of employing an identification strategy that deals with the before and after differences in electricity consumption of households remained in the traditional tariff structure (i.e., a flat price of 14.1 cents for all hours).

Because the CER experiment dataset primarily utilized in the following empirical analysis was generated from a carefully developed randomized controlled trial (RCT), in principle, the effect of the TOU tariffs on household electricity consumption can be measured simply through the difference in average usage between the two groups during the treatment period.[10] However, due to the non-trivial difference in electricity demand between the control and treatment groups during the baseline period, I follow the previous studies utilizing the same experiment and employ a difference-in-differences (DID) approach to estimate the electricity savings caused by the TOU pricing program.

I include the temperature as an explanatory variable directly in my econometric models. In the previous papers using the identical dataset, fixed effects (FEs) were utilized to control for time-varying factors that influenced household electricity consumption. Since those studies focused on quantifying how households responded, on average, to the TOU price regimes newly introduced, adding such FEs to their models served their research purpose. In other words, they did not need to explicitly model the relationship between temperature and household electricity consumption to estimate the average treatment effects (ATEs). However, a primary interest of this research is to understand how electricity savings vary with the temperature after shifting to TOU prices. Therefore, more direct controls rather than FEs, not sweeping out temperature variations across days, are required in my empirical analysis. For that reason, I extend the typical panel DID specification and allow the treatment effect to vary as a function of the daily average temperature.[11] That is, I estimate the ATEs of

[9] In Panel A, non-treated households consumed more electricity during the baseline period, especially on days with higher heating needs. The fact that the total HDDs during the baseline period were generally greater than those during the treatment period for a given temperature bin could explain the phenomenon.

[10] Because random assignment of participating households puts selection bias right, observed differences in electricity consumption between the control and treatment groups after introducing the TOU tariffs are only attributable to their differences in exposure to the time-varying electricity prices.

[11] Under three identifying assumptions, applying the DID strategy to measure energy savings obtained from adopting the TOU prices makes sense. First, the parallel trend assumption is required for the DID estimator. Considering that the 30-minute interval meter reads for participating households were collected from a trial, the assumption means that the pre-treatment-period load profile for the treated households should be very similar to that for the non-treated households. FIGURE A showing average within-day load profiles for the two groups during the baseline period supports the plausibility of the parallel trend assumption. In addition, the electricity consumption profile for the control group illustrated in FIGURE B, which smoothly evolved over the entire experiment period although heavily fluctuated day to day, suggests its high reliability as a counterfactual under the assumption.

The second identifying assumption necessary for the plausibility of the identification strategy employed is the assumption of common temporal shocks. This assumption implies that a treatment-status-irrelevant unexpected event occurring at the same time as or following the deployment of the dynamic prices should have the same impact on both the control and treatment groups. Although the common shocks assumption cannot be tested directly, the similar trends in electricity demand profiles for the control and treatment groups shown in FIGURE B support the assumption required for the DID approach.

the dynamic prices on household electricity demand by exploiting the within-household electricity consumption changes across not only periods but temperatures.[12]

Figure 5: Summary Statistics and Differences in Means for Treatment and Baseline Periods

3 Empirical Analysis and Results

3.1 Household Average Responses to Time-Of-Use Prices

3.1.1 Half-Hourly Average Treatment Effects

Utilizing a panel DID identification strategy, I first measure the impact of the TOU prices on 30-minute-interval household electricity consumption. To obtain the ATE for each half-hour interval, I estimate the following specification:

$$kWh_{itw} \ = \ \beta_w \mathbb{1}\big[\text{Treatment \& Post}\big]_{it} \ + \ \alpha_{iw} \ + \ \gamma_{dw} \ + \ \delta_m \ + \ \epsilon_{itw} \tag{1}$$

The term kWh_{itw} is the electricity consumption by household i on the day t during the half-hourly time window w. The indicator variable $\mathbb{1}\big[\text{Treatment \& Post}\big]_{it}$ is equal to 1 only if household i is in the treatment group and the day t is in the treatment period. The terms α_{iw}, γ_{dw}, and δ_m are household-by-half-hourly-interval, day-of-week-by-half-hourly-time-window, and month-of-year fixed effects, respectively. In the specification, the point estimates of β_w representing the ATE for each 30-minute interval w are the parameters of interest. I cluster the standard errors at the household and the day of experiment levels to correct for serial correlation.

Figure 6: Half-Hourly Average Treatment Effects

Figure 6 summarizes the estimated ATEs in the form of a time profile. As also demonstrated in Prest (2020), peak hours (i.e., from 5:00 p.m. to 7:00 p.m.), during which the inefficiency of fixed flat-rate tariffs is greatly intensified,

Third, the stable unit treatment value assumption (SUTVA) must hold too. The SUTVA requires that introducing TOU prices did not affect the electricity consumption of the untreated households. That is, the SUTVA allows no spillovers. During the recruitment process, the locational distribution of the participating households was aligned with that of the total Irish population to construct a representative sample of the national population. Because only a few thousand households scattered geospatially participated in the nationwide experiment, it is unlikely that the treated households influenced the households allocated to the control group. This again supports the SUTVA required under the DID identification strategy.

[12] The attrition rate during the RCT was about 20%. The main reasons for participant attrition were changes in tenancy and supplier. Due to the imperfect compliance, the estimates must be interpreted as local average treatment effects (LATEs). However, according to CER (2011), attrition was unlikely to be associated with the RCT. Furthermore, the level of attrition varied only marginally across treatment status.

show dominant electricity savings. In the following empirical analysis, I continually focus on household electricity demand responses to the time-varying prices during the peak rate period.

3.1.2 Hourly Average Treatment Effects in the Peak Rate Period

Estimating peak-rate-period ATEs relative to the control group allows us to know whether or not the law of demand is satisfied between the responsiveness of Irish households and the magnitudes of price changes in TOU electricity pricing.[13] To do so, I run the following regression for each of the four tariff groups:

$$kWh_{ith} \;=\; \beta_p \mathbb{1}\big[\text{Treatment \& Post}\big]_{it} \;+\; \alpha_{iw} \;+\; \gamma_{dw} \;+\; \delta_m \;+\; \epsilon_{ith} \tag{2}$$

Excepting the dependent variable and the parameter of interest, the econometric model above is the same as (1). Specifically, the response variable kWh_{ith} means the electricity consumption by household i on the day t during the hour of the day h, and the point estimates of β_p indicate the ATE for each of three rate periods p. Table 4 summarizes the regression results.

The results demonstrated in Table 4 indicate that the measured ATEs generally follow the law of demand: in general, the reduction in household demand for electricity during the peak rate period grows with the size of the price jump. Importantly, the results imply that household electricity savings from temperature-control use or ones from non-temperature-control uses depend on the amount of the tariff change in the peak rate period. Motivated by this implication, the relative responsiveness of the two distinct drivers of energy savings to the time-varying prices introduced is quantified below.

Table 4: Average Treatment Effects in the Peak Rate Period

[13] In this paper, the effects of four different information stimuli on household electricity consumption are not of interest. Pon (2017) studied the effects in detail using the same datasets.

	Hourly Electricity Consumption (kWh/Hour)			
	(1)	(2)	(3)	(4)
$\mathbb{1}$[Treatment & Post]	-0.136^{***}	-0.168^{***}	-0.161^{***}	-0.210^{***}
	(0.015)	(0.023)	(0.015)	(0.023)
Tariff Group	A	B	C	D
FEs: Household by Half-Hourly Time Window	Yes	Yes	Yes	Yes
FEs: Day of Week by Half-Hourly Time Window	Yes	Yes	Yes	Yes
FEs: Month of Year	Yes	Yes	Yes	Yes
Observations	1,771,600	1,147,240	1,795,680	1,155,840
Adjusted R^2	0.360	0.376	0.362	0.360

Note: (...)

3.2 Breakdown of Peak-Rate-Period Household Responses to Time-Of-Use Prices

3.2.1 Breakdown of Household Responses in the Peak Rate Period

I decompose the TOU-tariff-causing reductions in household electricity consumption during the peak rate period into two parts to determine the share of energy savings stemming from two different sources: savings from non-temperature-control and temperature-control uses. Here, the non-temperature-control-related electricity savings mean the stable savings that occur every day regardless of each day's heating degrees. That is, the savings associated with non-temperature-control electricity use do not vary across days. On the contrary, the latter savings strictly depend on HDDs, which fluctuate daily. Therefore, the temperature-control-related electricity savings are additional savings that appear on days with positive HDDs due to reductions in electricity consumption for heating. Isolating the impact of TOU prices on household electricity demand for temperature-control use from the total reductions in electricity demand enables us to know how differently the TOU tariff structures function from day to day, whose implications will be discussed in the next section.

To break down peak-hours household responses to TOU prices, I exploit the following econometric model inspired by the DID framework:

$$\begin{aligned} kWh_{ith} \ = \ & \beta_1 HDD_t \ + \ \beta_2 HDD_t \cdot \mathbb{1}\left[\text{Treatment}\right]_i \\ & + \ \beta_3 \mathbb{1}\left[\text{Post}\right]_t \ + \ \beta_4 HDD_t \cdot \mathbb{1}\left[\text{Post}\right]_t \\ & + \ \beta_5 \mathbb{1}\left[\text{Treatment \& Post}\right]_{it} \ + \ \beta_6 HDD_t \cdot \mathbb{1}\left[\text{Treatment \& Post}\right]_{it} \\ & + \ \alpha_{iw} \ + \ \gamma_{dw} \ + \ \delta_m \ + \ \epsilon_{ith} \end{aligned} \tag{3}$$

Like (2), the dependent variable kWh_{ith} is the electricity consumption by household i on the day t during the hour of the day h. There are three indicator variables in the model: the first indicator variable $\mathbb{1}[\text{Treatment}]_i$ has the value of 1 if household i is assigned to the treatment group; the second indicator variable $\mathbb{1}[\text{Post}]_t$ equals 1 when the day t is in the treatment period; the last indicator variable $\mathbb{1}[\text{Treatment \& Post}]_{it}$ is equal to 1 only for treatment households during the treatment period. The model also includes interaction terms between daily HDDs and those indicator variables. The terms α_{iw}, γ_{dw} and δ_{mw} are household-by-half-hourly-time-window, day-of-week-by-half-hourly-time-window and month-of-year-by-half-hourly-time-window fixed effects, respectively.

The primary coefficients of interest in (3) are β_5 and β_6. Both coefficients show how much electricity consumption households have reduced since the deployment of the TOU tariffs. To be specific, β_5 is the decrease in household electricity consumption for non-temperature-control uses, while β_6 is associated with the reductions in electricity consumed to satisfy household heating needs for given HDDs.

Using the points estimates of the two coefficients of interest presented in Table 5, I show how the electricity savings caused by the TOU prices vary with daily HDDs in Figure 7.[14] The figure clearly demonstrates that the households assigned to the treatment group significantly reduced their electricity consumption when they were subject to the TOU prices. Specifically, they reduced their consumption by about 10% on a day with zero HDD. In addition, it is evident from the figure that the share of temperature-control-use-related demand reductions grows as household electricity needs for heating become serious. For example, the energy savings originating from electricity consumption for temperature-control use were close to half of the total TOU-pricing-inducing reductions in household electricity demand when Irish household needs for heating were at their peak (i.e., around daily HDDs of 35).

[14] In Table 5, the second column demonstrates the estimates $\hat{\beta}_5$ and $\hat{\beta}_6$ obtained from the econometric model (3). The first and the third columns are for robustness checks. As shown in the first column, adding household-level FEs instead of the indicator variable for assignment to the treatment group leads to the almost same regression result. The third column indicates that excluding covariates associated with the indicator variable for the treatment period results in very minimal changes in point estimates.

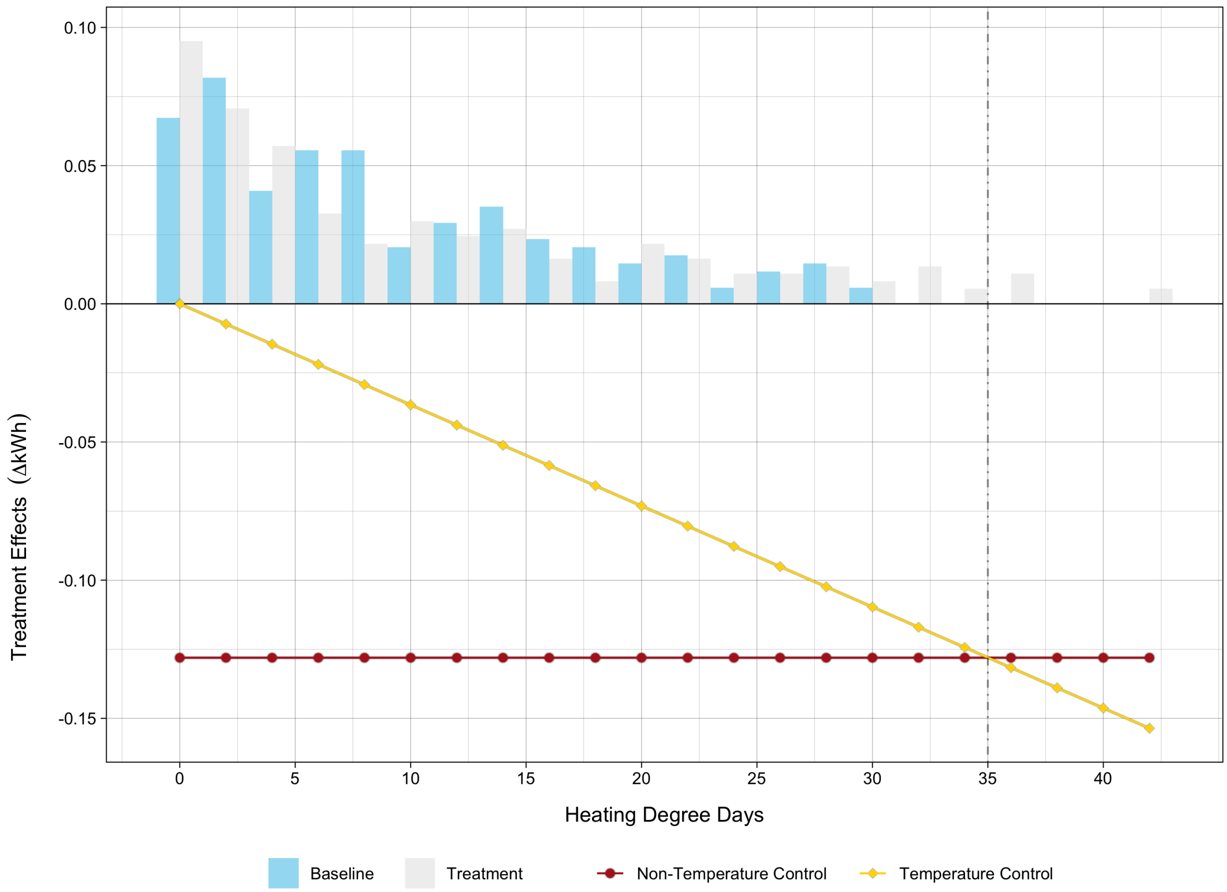

Figure 7: Breakdown of Hourly Average Treatment Effects

The specification (3) is also utilized to examine the relationship between the degree of price increases and the electricity savings during the peak rate period. The point estimates of coefficients of interest, demonstrated in the last four columns of Table 5, are interesting in two points. First, the reduction in non-temperature-control electricity demand caused by introducing the TOU tariffs is positively proportional to the size of the change in price during peak hours. In other words, the electricity savings occurring on any day regardless of the average daily temperatures obviously follow the law of demand. Second, the savings associated with temperature-control electricity use are insensitive to the price jumps in the peak rate period.

Table 5: Breakdown of Average Treatment Effects in the Peak Rate Period

	Hourly Electricity Consumption (kWh/Hour)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HDDs	0.005**	0.005**	0.004**	0.004*	0.006***	0.006**	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
𝟙[Treatment]	0.077***						
	(0.030)						
𝟙[Treatment] × HDDs	0.003**	0.003**	0.004**	0.005***	0.004	0.002	0.001
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
𝟙[Post]	0.001	0.001		0.00002	0.002	0.001	0.001
	(0.018)	(0.019)		(0.019)	(0.019)	(0.019)	(0.019)
𝟙[Post] × HDDs	−0.001	−0.001		−0.0005	−0.001	−0.001	−0.001
	(0.002)	(0.002)		(0.002)	(0.002)	(0.002)	(0.002)
𝟙[Treatment & Post]	−0.128***	−0.128***	−0.127***	−0.099***	−0.122***	−0.138***	−0.182***
	(0.015)	(0.016)	(0.015)	(0.019)	(0.026)	(0.019)	(0.025)
𝟙[Treatment & Post] × HDDs	−0.004***	−0.004***	−0.004***	−0.004***	−0.005***	−0.003*	−0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Tariff Group	All	All	All	A	B	C	D
FEs: ID by Half-Hourly Time Window	No	Yes	Yes	Yes	Yes	Yes	Yes
FEs: Day of Week by Half-Hourly Time Window	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs: Month of Year by Half-Hourly Time Window	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,522,560	3,522,560	3,522,560	1,771,600	1,147,240	1,795,680	1,155,840
Adjusted R^2	0.051	0.366	0.366	0.361	0.377	0.362	0.360

Note: (...)

3.2.2 Peak-Rate-Period Household Responses as a Linear Function of Price Changes

(1. Description of average responses in the peak period: linear function of changes in unit rate)

(1.1. Econometric model)

$$(...) \tag{4}$$

(1.2. Results, with implications)

Table 6: Treatment Effects as a Linear Function of Unit Rate Changes

4 Time-Of-Use Prices with Higher Granularity

4.1 Time-Of-Use Prices with 2-Dimensional Dynamics

4.1.1 Time-Of-Use Prices with an Additional Dynamics in Heating Needs

(1. Inefficiency of time-invariant prices)

(2. TOU prices with an additional dynamics)

(2.1. Description of TOU prices with an additional dynamics)

(2.2. Validity of TOU prices with an additional dynamics)

(2.2.1. Little evidence of load shifting, implying that consumption during the peak period is the key to reduction in electricity consumption)

(2.2.2. High demand for electricity on days with high HDDs)

4.1.2 Comparison to Alternative Dynamic Prices

(1. Key differences)

(1.1. From other dynamic prices, especially in terms of granularity)

(1.2. From TOU, especially in terms of the additional dynamics)

(2. Advantages of TOU prices with an additional dynamics)

(2.1. Less welfare loss on days with less HDDs)

(2.2. High efficiency on days with high HDDs, especially during the peak period)

4.2 Simulations

(1. Description of Simulations)

(2. Simulation results, with their implications)

Figure 8: Simulated Treatment Effects

5 Conclusion

(...)

A Appendixes

A.1 For Chapter 1

(...)

A.2 For Chapter 2

(...)

A.3 For Chapter 3

(...)

References

Commission for Energy Regulation. 2011. "Electricity Smart Metering Customer Behaviour Trials (CBT) Findings Report."

Liu, Xiaochen, and John Sweeney. 2012. "The Impacts of Climate Change on Domestic Natural Gas Consumption in the Greater Dublin Region." *International Journal of Climate Change Strategies and Management*, 4(2): 161–178.

Pon, Shirley. 2017. "The Effect of Information on TOU Electricity Use: An Irish Residential Study." *Energy Journal*, 38(6): 55–79.

Prest, Brian C. 2020. "Peaking Interest: How Awareness Drives the Effectiveness of Time-of-Use Electricity Pricing." *Journal of the Association of Environmental and Resource Economists*, 7(1): 103–143.