1 Introduction

Many energy utilities are shifting customers onto Time-Of-Use (TOU) electricity rate structures, which have become feasible owing to the diffusion of smart metering technology.[1] Under a TOU tariff structure, the retail price of electricity varies across periods of the day—typically with a higher "peak" price during the late afternoon hours and lower "off-peak" prices during other hours. These TOU rates are intended to reduce electricity consumption during the peak demand hours of the day when the cost of supplying the electricity and the capacity constraints on transmission networks are at their greatest. In addition to reducing peak demand for electricity, TOU pricing can also provide cost savings by shifting some of the consumption to lower demand hours or hours with excess renewable output.

Ultimately, the cost savings that can be achieved by TOU tariff structures depend on two factors. First, the extent to which TOU rates can reduce electricity consumption during peaks, and shift consumption across time, relies on how elastic consumers are to the magnitude of the price increase in the peak demand hours and the price decreases in the off-peak hours. In settings where households are unresponsive to within-day price variations, TOU prices may provide only small gains. Second, the magnitude of the benefits achieved by TOU tariffs also depends on how the resulting reductions in electricity consumption differ across days. Intuitively, reducing electricity consumption will provide larger cost savings on days with very high electricity demand (e.g., days with extreme temperatures when demand for temperature control peaks). Suppose TOU tariffs merely cause a uniform reduction across days (e.g., households turn off their lights more often). In that case, the benefits from the time-varying rates will not vary across days. In contrast, if TOU rates induce households mainly to reduce their electricity consumption for heating or cooling, then the reductions in household electricity consumption are likely to be concentrated on peak demand days when the reductions will be the most valuable.

In light of those factors, it is necessary not only to examine how responsive a household's aggregate consumption is to the magnitude of the peak vs. off-peak price changes, but also to decompose how much of the savings in household electricity consumption stem from reductions in the use of energy services that systematically vary across days (e.g., temperature control), in order to fully understand the full impacts of TOU electricity pricing on household electricity consumption.

While many evaluations of various dynamic electricity prices, including TOU programs, consistently document reductions in electricity consumption during peak hours (Faruqui and George, 2005; Faruqui and Sergici, 2011; Faruqui, Sergici and Akaba, 2013), the literature often finds that households' consumption is quite inelastic to the magnitude of the within-day price changes (Allcott, 2011; Jessoe and Rapson, 2014). Notably, Prest (2020) finds that, in a TOU pricing experiment in Ireland, households were highly insensitive to the incremental increases in the peak rate.[2] That is, residential consumers seemed to respond only to the existence of the within-

[1]According to Faruqui, Hledik and Sergici (2019), residential TOU rates were offered by about 15% of all America's utilities in 2019.

[2]This paper, which also utilizes the CER experiment datasets, expresses the results as follows: "Most of the overall response comes at the smallest price increase, with higher prices yielding strongly diminishing returns."

day price changes and not the magnitude of the within-day price changes. This paper aims to re-examine the TOU program evaluated by Prest (2020) to understand why household's aggregate consumption is so inelastic with respect to the magnitude of the within-day price changes.

When re-measuring how sensitive residential consumers are to TOU tariffs, I decompose their electricity consumption into two distinct channels of consumption instead of merely investigating their consumption as a whole: 1) electricity consumption for non-temperature-control uses (e.g., lighting, operating appliances, and cooking), and 2) electricity consumption for temperature-control uses (e.g., cooling and heating). My empirical analysis focuses on those two broad categories of electricity consumption for two reasons. First, the two types of electricity consumption react differently to outdoor temperatures. Electricity consumed for temperature control will undoubtedly depend on outdoor temperatures. For example, more electricity will be used to heat on cold days compared to mild days. By contrast, electricity used for other non-temperature-control services will be largely independent of outdoor temperatures. These enable me to estimate how much electricity is consumed for each category by using temperature variation. Second, the two distinct electricity consumption categories may respond differently to TOU prices. For instance, TOU electricity pricing may cause households to relocate some non-temperature-control-driven services to non-peak hours without changing aggregate consumption across a day (Herter and Wayland, 2010; Harding and Lamarche, 2016). In contrast, if TOU rates induce them to lower their electricity use for heating, then there could be reductions in consumption across all hours.

My study examines 30-minute interval household metering data collected from a TOU pricing experiment conducted from July 2009 to December 2010 by the Commission for Energy Regulation (CER), the electricity and natural gas sector regulator in Ireland.[3] While the vast majority of homes in the sample utilized oil and gas as their primary energy source for space and water heating, a sizable amount of electricity was still used for heating in those homes. Notably, residential electricity consumption peaked during the winter months, typically reaching levels approximately 1.5 times higher than the consumption observed during the mild summer months. Using the observed household consumption throughout the day and measurements of the daily temperatures in Ireland, I estimate 1) the changes in temperature-control-driven and non-temperature-control-driven consumption, respectively, caused by the TOU program, 2) how these consumption changes vary with the average daily outdoor temperature—more precisely, daily Heating Degree Days (HDDs)—, and 3) how these consumption changes vary with the magnitude of the peak-rate-period price change.

From my empirical analysis, I document two key findings. First, the two broad categories of household electricity consumption were responsive to incremental changes in the peak-rate-period price, but in different ways. In the peak rate period, households' non-temperature-control-driven electricity consumption was highly sensitive to the magnitude of the price changes. On the other hand, there is no evidence that the reduction in temperature-control-driven electricity consumption during the peak rate period increased as the size of the incremental price changes grew. Instead, there is weak evidence demonstrating that in the peak rate period,

[3]The CER changed its name to the Commission for Regulation of Utilities (CRU).

the reduction in temperature-control-driven electricity consumption went towards zero as the price increased. Interestingly, due to the opposite relationship between demand reductions and price changes in the two channels of electricity consumption, the high sensitivity of household electricity consumption in response to TOU pricing in the peak rate period was masked. In other words, when the estimated reductions in electricity consumption originating from the two channels are aggregated, the difference in the combined reduction between tariff groups is seemingly dampened because of the opposite correlations.[4] Indeed, this finding precisely explains the price insensitivity discussed in Prest (2020).[5]

Even in the hours leading up to and following the peak rate period (denoted the pre- and post-peak hours/periods, respectively), the TOU tariffs also induced changes in households' demand for electricity, which cannot be explained simply by price drops in the hours surrounding the peak rate period. In the experiment, the households under the TOU tariff structures experienced price increases during the peak hours, whereas they faced decreases in the price they paid for electricity consumption in the hours surrounding the peak rate period. Moreover, the higher the price the households had to pay in the peak rate period, the lower the off-peak prices (i.e., the day and night rates) they had to pay. My regression analysis shows that households reduced their non-temperature-control-related electricity consumption in both off-peak periods. In other words, the load-shedding in the peak rate period spilled over into the pre- and post-peak hours, during which prices fell. On top of that, load-shifting from the peak to the off-peak hours, incentivized by across-rate-period price differences, seemed to occur, too. Furthermore, the revealed relationship between the size of the load-shifting and the magnitude of the peak-hour price change confirms the economic intuition about the price incentive for the load relocation. My analysis also suggests that the load-shifting only partly, or just barely, offset the spillovers. In the aggregate, in both off-peak periods, the more considerable the price increase in the peak rate period, the smaller the reduction.

For temperature-control-driven consumption changes, my empirical analysis indicates that a different pattern emerged in pre- and post-peak hours. I find that during the pre-peak hours, households' temperature-control-driven electricity usage fell, and those reductions got larger as the magnitude of the price jump in the peak rate period increased. That is, households exposed to a higher peak-demand-hour price appeared to reduce their pre-peak usage for heating by larger amounts. In contrast, my analysis demonstrates that households' temperature-control-driven electricity usage rose during post-peak hours. As opposed to the consumption changes in the pre-peak hours, these growths in electricity usage for heating during the post-peak hours got smaller as the size of the peak-hour price change increased. Altogether, in both non-peak periods, due to the opposite directional changes in the two categories of household electricity consumption, households' sensitive responsiveness to the TOU tariff structures was muted, as it was in the peak rate period. Interestingly, those temperature-control-relevant consumption changes near the peak rate period were observable only when outdoor temperatures were low enough.

[4]There were four tariff groups in the CER experiment. See Figure 1.
[5]See *5.3 Price Insensitivity* in Prest (2020).

The second key finding from my empirical analysis is that the reduction in households' temperature-control-related electricity consumption during the peak hours showed a U-shaped profile over daily HDDs. The nonlinearity in TOU-tariff-induced temperature-control-associated reduction in household electricity consumption over households' daily heating needs discloses a veiled feature of TOU electricity pricing: its day-varying effects on the temperature-control-related part of residential electricity consumption. Suppose that the reductions obtained by adopting TOU prices stem entirely from the non-temperature-control use of electricity. In that case, the degree of reductions does not vary across days because it is nearly irrelevant to across-day temperature variation. My empirical results, however, indicate that on days with moderate heating needs, a sizable reduction in household electricity consumption stemmed from electricity usage for temperature control during the peak hours. For instance, in the case of the household subgroup that experienced a six-dollar price increase in the peak rate period, more than two-thirds of the reduction in their electricity consumption came from temperature-control-related consumption when the value of daily HDDs was ten. Consequently, even though the TOU electricity pricing only has intraday price variation, the pricing already induces a substantial reduction in electricity consumption for heating on typical winter days, in terms of daily HDDs, in Ireland. Therefore, on those days, the additional gains captured by switching TOU prices to Real-Time Pricing (RTP) will likely be smaller than many economists have thought.[6]

To sum up, the results from my empirical analysis extend the previous work by isolating temperature-control-associated reduction in household electricity consumption from the entire TOU-tariff-induced demand declines. My results demonstrate that in and near the peak hours, the changes from each of the two channels of electricity consumption are responsive to the magnitude of the price changes in the peak rate period. That is, in determining the electricity consumption level within a home under TOU tariff structures, not the mere existence of price changes, prices themselves—more clearly, the magnitude of the price increase in the peak hours—still matter. Moreover, the day-varying performance of TOU electricity pricing suggests a vital policy implication of an alternative electricity pricing that internalizes an additional layer of dynamics by nonlinearly synchronizing price increases in the peak hours with daily HDDs, causing a more significant reduction in household electricity consumption on extremely cold days.

2 Data

2.1 Description of CER Experiment

The Commission for Energy Regulation (CER), the regulator for Ireland's electricity and natural gas sectors, conducted the Smart Metering Electricity Consumer Behavior Trial (hereafter, the "trial") between July 2009 and December 2010.[7] As part of the Smart Metering Project initiated in 2007, the trial's purpose was to assess

[6] Under RTP, retail prices vary across not only hours of days but days according to contemporaneous generating costs.
[7] The detail about the CER experiment presented hereinbelow is a summary of Commission for Energy Regulation (2011).

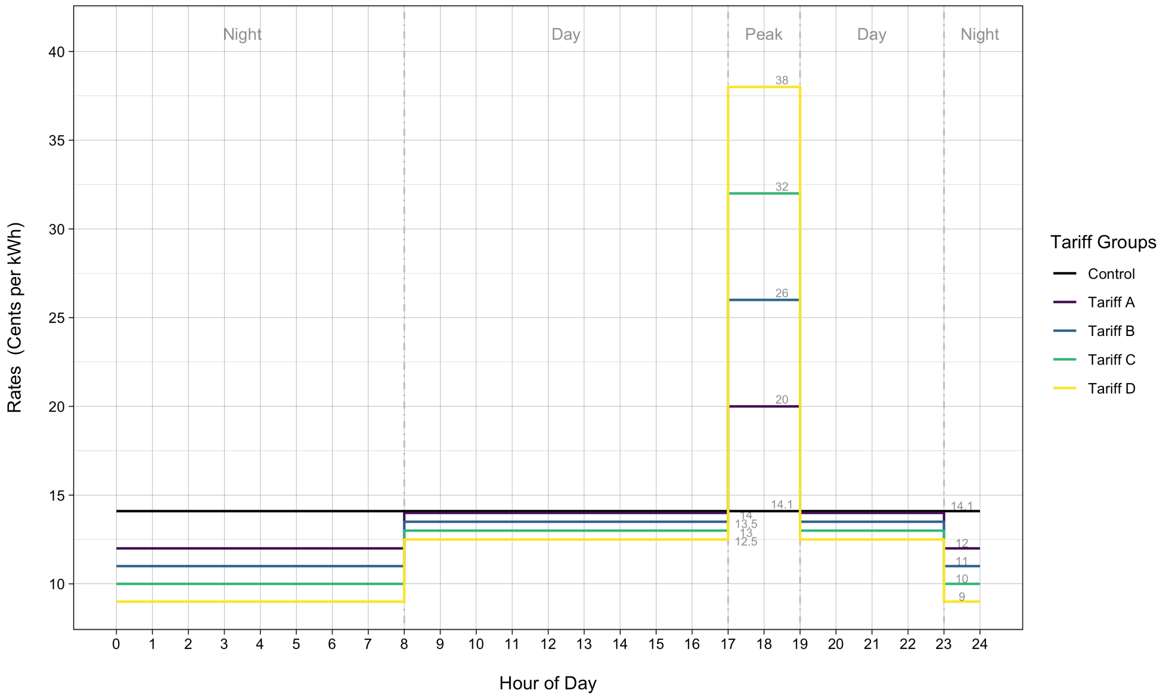

Figure 1: Time-Of-Use Pricing Structures

Note: This figure illustrates the CER experiment in terms of TOU tariff structures. The households in the control group were subjected to a flat rate (i.e., 14.1 cents per kWh) during the entire experiment period. On the contrary, the treated households are assigned to one of four TOU tariff groups. And for each tariff group, there were three rate periods: night, day, and peak. Only the unit rate in the peak rate period was higher than the flat rate.

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.[8]

The households who voluntarily opt-in to the experiment were randomly assigned to control and treatment groups.[9] 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 four DSM

[8]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.

[9]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 include electricity consumption data only for 4,225 households.

Both papers point out that voluntary opt-in might cause bias in the estimated treatment effect. Refer to *5.5.3 External Validity* in Prest (2020) and *5.1 Addressing Self-Selection* in Pon (2017).

Table 1: Treatment and Control Group Assignments

Stimuli	Tariffs					Total
	Control	A	B	C	D	
Monthly Bill	0	79	37	89	28	233
Bi-Monthly Bill	0	81	34	76	34	225
Bi-Monthly Bill + IHD	0	79	22	86	30	217
Bi-Monthly Bill + OLR	0	90	27	84	34	235
Control	260	0	0	0	0	260
Total	260	329	120	335	126	1,170

stimuli, described in detail later. 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.[10] 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 from 11:00 p.m. to 8:00 a.m. As illustrated in Figure 1, the order of magnitude in rate changes during 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 received their bills in 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.[11]

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

[11] 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.

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.[12]

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 the energy savings 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 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 a longitudinal sample that consists of observations satisfying certain conditions only. First of all, the sample is constructed by including observations only for the second half of each experiment period.[13] From this sample, I keep observations for non-holiday weekdays in the published electricity consumption data because the TOU rates were active just on those days. And then, only households that continuously exploited non-electric fuels for their space and water heating during the experiment periods (i.e., the baseline and the treatment periods) are preserved in the sample.[14] Moreover, among the non-electric-heating households, those with unreliable meter reads are excluded from the sample. This process results in 1,170 households. Table 1 summarizes the assignment distribution of the 1,170 households.

The control and treatment groups in the sample are largely balanced, as shown in Table 2. Although several variables are statistically significant at the 5% level, the Bonferroni familywise p-value is not significant at that level. The absence of differences between the two groups over many observables are consistent with previous studies examining the CER experiment dataset.[15]

[12] Many papers have explored the CER dataset with different focuses. See Carroll, Lyons and Denny (2014), McCoy and Lyons (2016), Cosmo and O'Hora (2017), and Di Cosmo, Lyons and Nolan (2014).

[13] I exclude the observations for the first half of the treatment period because there is no counterpart observation in the baseline period.

[14] From the survey data, it is possible to find out what type of fuel each responding household used for each heating purpose during each period.

There are two reasons why only non-electric-heating households are exploited in the following empirical analysis. First, in Ireland, non-electric fuels, such as oil, gas, and solid fuels, fulfill most of the residential heating demand. Specifically, according to Sustainable Energy Authority of Ireland (2022), only 4% of Irish households utilize electricity to heat their space and water. Therefore, with respect to fuels for heating in Ireland, the sample consisting of non-electric heating households only is representative. Second, as Figure 3 demonstrates, even non-electric-heating households consumed more electricity as temperatures decreased. In other words, electricity is still essential for non-electric-heating households to warm their space or water. Hence, the sample, including non-electric-heating households only, is well aligned with one of the primary purposes of this research: to evaluate the impact of TOU pricing on temperature-control-driven residential electricity consumption separately.

[15] 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).

Table 2: Summary Statistics and Differences in Means

	Control		Treatment		Difference		
	Mean	(S.E.)	Mean	(S.E.)	Mean	(S.E.)	p-value
Electricity Consumption during Baseline Period (kWh)							
Daily	22.122	(0.674)	23.529	(0.379)	1.407	(0.773)	0.069
Hourly	0.939	(0.028)	0.996	(0.016)	0.057	(0.032)	0.074
Hourly, Night Rate	0.524	(0.018)	0.560	(0.010)	0.035	(0.021)	0.088
Hourly, Day Rate	1.128	(0.034)	1.193	(0.019)	0.065	(0.039)	0.095
Hourly, Peak Rate	1.537	(0.053)	1.642	(0.029)	0.105	(0.060)	0.080
Demographics							
Age Group: 65+?	0.277	(0.028)	0.225	(0.014)	-0.052	(0.031)	0.096
Education: Primary or less?	0.208	(0.025)	0.144	(0.012)	-0.064	(0.028)	0.022
Education: Secondary?	0.462	(0.031)	0.457	(0.017)	-0.005	(0.035)	0.889
Unemployed?	0.081	(0.017)	0.101	(0.010)	0.020	(0.020)	0.304
Number of People over 15 in Home	2.488	(0.061)	2.506	(0.032)	0.019	(0.077)	0.808
Number of People under 15 in Home	1.754	(0.060)	1.964	(0.035)	0.210	(0.138)	0.132
Housing Characteristics							
Owned House?	0.904	(0.018)	0.932	(0.008)	0.028	(0.020)	0.165
Number of Bedrooms	3.335	(0.054)	3.465	(0.028)	0.130	(0.061)	0.035
Timer for Space Heating	0.792	(0.025)	0.802	(0.013)	0.010	(0.028)	0.728

Note: In the table, variable descriptions with question mark suggest that these variables are binary.

2.3 Description of Weather Data

In this research, weather data are an essential element. The main interest of most TOU papers has been to measure how consumers respond to TOU prices or the heterogeneity in their responsiveness across different information stimuli. And the studies have focused on aggregate electricity consumption, consisting of consumption for a wide range of end-use types. Hence, those studies usually do not control 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 electricity usage due to seasonal changes. On the other hand, a novel approach adopted in this paper is to decompose household electricity consumption into two broad categories: non-temperature-control- and temperature-control-associated electricity consumption.[16] Since the electricity consumption for temperature-control use is significantly driven by weather, particularly temperatures, it is necessary to link the 30-minute interval consumption data with reliable weather data that is of an appropriate level of resolution.

I utilize average daily temperatures in my empirical analysis. More granular temperatures, like hourly

[16]Details of the approach are discussed in Section 3.2.1.

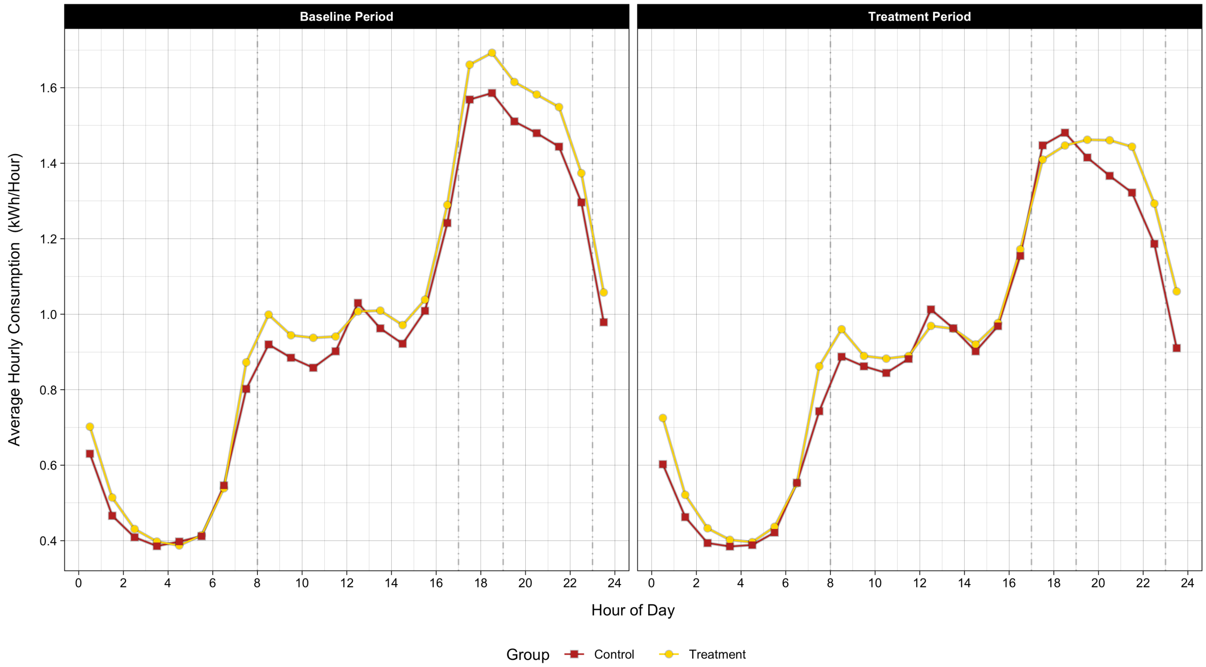

Figure 2: Average Hourly Electricity Consumption by Time of Day

Note: The figure shows, during each experiment period, household average hourly electricity consumption for the control and treatment groups, respectively. In general, during the baseline period, households assigned to the treatment group consumed more electricity at a given hour of the day. Although both groups reduced their electricity consumption during the treatment period, the reduction in electricity consumption for the treatment group was much more remarkable for the treatment group than for the control group.

temperatures, are not a dominant determinant of temperature-control-driven electricity consumption at a point in time. It is not easy to believe that households adjust their electricity consumption according to ever-changing outside temperatures elaborately and instantly.[17] 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-induced reductions in electricity consumption conditional on the average heating needs on a given calendar day.

I exploit hourly temperature data for the Dublin airport weather station, provided by Met Éireann, Ireland's National Meteorological Service, to compute average daily temperatures. There is no available location information in the published CER experiment dataset for privacy and security reasons. Therefore, it is impossible to match a participant's consumption data with the 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. Because of this, I use the mean daily temperatures obtained by averaging the Dublin airport station's hourly temperatures as the representative temperatures in the following analysis.

[17] Refer to *3.4 Household Response to Dynamic Prices Exhibits Nontrivial Costs of Action That Impede Peak Reductions* in Harding and Sexton (2017).

Using the average daily temperatures, I calculate daily Heating Degree Days (HDDs). Instead of 65 degrees of Fahrenheit ($^{\circ}F$), a normal base temperature in the United States, $60^{\circ}F$ is utilized to compute daily HDDs, according to Liu and Sweeney (2012). The evolving pattern of temperature-control-driven demand for electricity on days with extreme temperatures could be significantly different under distinct rate structures—e.g., flat and TOU rates. If this is true, the lack of counterfactual consumption observations will cause bias in the measured impact of introducing TOU pricing on household electricity consumption. So, I drop observations for those days in the treatment period when constructing the sample to address the potential threat to the identification.

2.4 Empirical Strategy

Figure 3, showing not only household average daily electricity consumption over temperature (in Panel A) but also percentage changes in electricity consumption (in Panel B), clearly demonstrates the motivation of this research.[18] As illustrated in Panel A of the figure, household demand for electricity grew gradually as the temperature decreased. That is, for Irish households, in addition to temperature-insensitive electricity demand (i.e., for non-temperature-control uses), there was a sizeable electricity demand for heating (i.e., for temperature-control uses), which seems to be highly responsive to temperature variations. In this research, I determine not only how much variations in household electricity consumption occurred, on average, in response to the deployment of the TOU tariffs but also how their impact varied according to daily HDDs. In other words, the dynamic-pricing-causing effects on for-heating and non-for-heating electricity uses are separately estimated to figure out the primary source of electricity savings. As shown in the figure, households in the control group consumed less electricity during the treatment period, especially on days with low temperatures, although their percentage reductions seem less than those of the treated households.[19] In light of this, it is necessary to employ an identification strategy that accounts for the before and after differences in household electricity consumption under the traditional tariff structure (i.e., a flat rate of 14.1 cents per kWh for all hours).

I employ a Difference-In-Differences (DID) approach to estimate the electricity savings caused by the TOU price program. The CER experiment dataset primarily utilized in the following empirical analysis was generated from a carefully developed Randomized Controlled Trial (RCT). So, 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.[20] However, as discussed, there exist non-trivial differences in electricity demand between the control and treatment groups during the baseline period. Following the previous studies exploiting the same data, I utilize a DID estimator to address the possible source of bias.

[18] 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.

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

[20] 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.

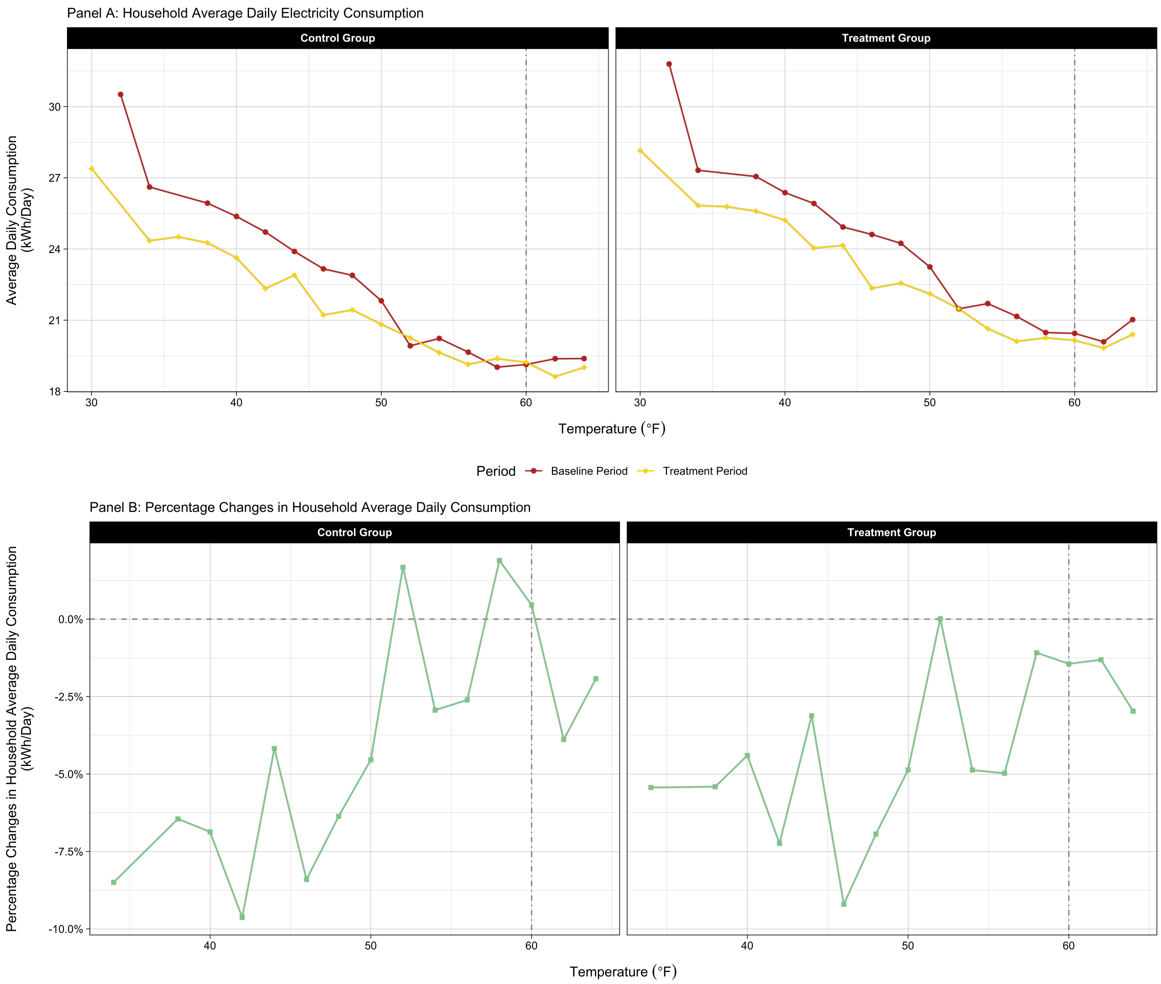

Figure 3: Pre- and Post-Treatment Household Average Daily Electricity Consumption

Note: Panel A in this figure illustrates, for each group, how within-household average daily electricity consumption evolved over average daily temperatures during each experiment period. In addition, Panel B of the figure demonstrates the percentage changes in residential electricity consumption after the deployment of TOU tariff structures at different mean daily temperatures. The treatment group showed larger percentage reductions on typical winter days (roughly speaking, when the average daily temperature was lower than the value of $45°F$), while the control group exhibited wider percentage reductions on exceptionally cold days in Ireland.

I include daily HDDs 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 influencing 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 a typical panel DID specification and allow the treatment effect to vary as a function of daily HDDs.

A caveat to my empirical analysis is that a tariff group in my sample's treatment group consists of four subgroups that were subject to one of the four different DSM stimuli. Because of this, part of the estimated ATEs should be attributable to the DSM stimuli. But as shown in Table 1, the proportions of the four distinct DSM stimuli, constituting each tariff group, are similar in my sample. Therefore, within a tariff group, a specific DSM stimulus is unlikely to play a prominent role in causing changes in household electricity consumption.

3 Empirical Analysis and Results

3.1 Household Average Responses to Time-Of-Use Electricity Pricing

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 Average Treatment Effect (ATE) for each half-hour interval, I estimate the following specification:

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

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_{tw}, and δ_m are household-by-half-hourly-interval, day-of-sample-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 4 summarizes the estimated ATEs in the form of a time profile. As already demonstrated in Prest (2020), peak hours (i.e., from 5:00 p.m. to 7:00 p.m.) show dominant electricity savings. The figure also demonstrates reductions in household electricity consumption not only in most of the meter readings prior to the peak rate period but also in three successive meter readings right after the period, even though the reductions, with two exceptions, are not statistically significant. The insignificant reductions in household electricity consumption are interesting because TOU prices in off-peak hours (i.e., prices in the night and day rate periods) were lower than the flat rate in the baseline period. The counterintuitive changes might indicate that households preemptively adjusted their consumption behavior to avoid the incident of paying higher prices. In other words, the peak-hour price increases under the TOU program were likely to cause some spillover effects in the hours leading up to and following the peak rate period. To explore whether households responded to the TOU program outside of the peak rate period as well or not, in the following empirical analysis, I will also pay

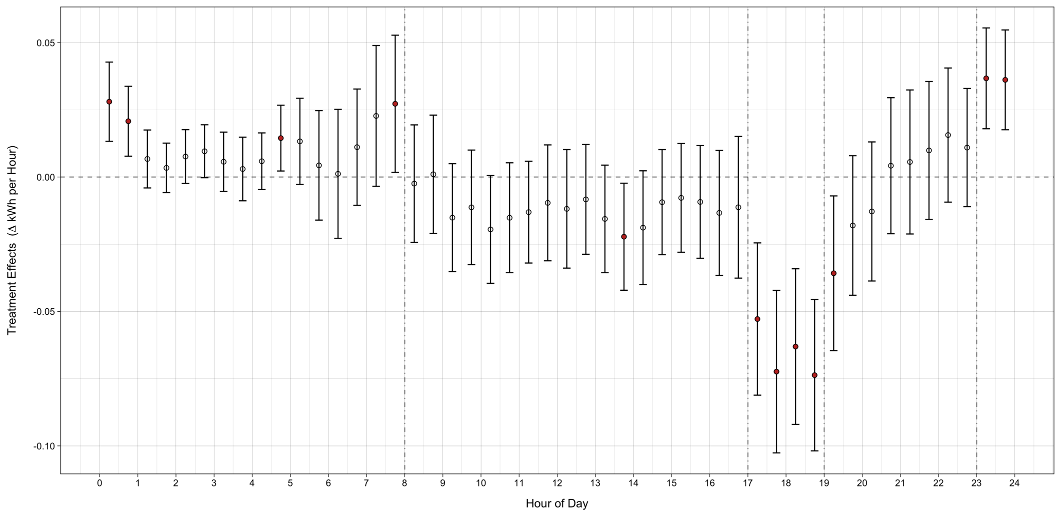

Figure 4: Half-hourly Average Treatment Effects

Note: This figure depicts the time profile of half-hourly average treatment effects with 95% confidence intervals. Standard errors are clustered at the household and date levels to adjust for serial correlation. As clearly illustrated, the treated households significantly reduced their electricity consumption during peak hours. A more interesting phenomenon is that they reduced their electricity consumption in hours leading up to and following the peak rate period, during which the applicable unit rate was lower than the flat rate in the baseline period, even though most of the estimated treatment effects are statistically insignificant in those hours.

attention to the off-peak hours, particularly the hours surrounding the peak rate period.

3.1.2 Hourly Average Treatment Effects in and near the Peak Rate Period

Estimating by-tariff-group ATEs in and near the peak rate period allows understanding how the relationship between the degree of change in household electricity consumption and the magnitude of a peak-demand-hour price increase evolves in and near the peak rate period.[21] To do so, I run the following regression for each of the four tariff groups:

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

Excepting the dependent variable and the parameter of interest, the econometric model above is the same as (1). Specifically, the response variable kWh_{ith}, which means the electricity consumption by household i on the day t during the hour of the day h, is utilized due to its better accessibility in interpretation. The point estimates of β_p indicate the ATE for each of the three intervals included in rate period p. Table 3 summarizes the regression results.

[21] 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.

Table 3: Hourly Average Treatment Effects in and near the Peak Rate Period

	Hourly Electricity Consumption (kWh/Hour)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbb{1}$[Treatment & Post]	−0.125***	−0.161***	−0.119***	−0.249***	−0.032***	−0.143***	−0.058***
	(0.020)	(0.036)	(0.022)	(0.044)	(0.011)	(0.015)	(0.015)
	[−0.165, −0.085]	[−0.231, −0.090]	[−0.163, −0.076]	[−0.336, −0.163]	[−0.055, −0.010]	[−0.173, −0.114]	[−0.087, −0.029]
Description of Period	Peak	Peak	Peak	Peak	Pre-Peak	Peak	Post-Peak
Period of Hours	17 to 18	17 to 18	17 to 18	17 to 18	15 to 16	17 to 18	19 to 20
Tariff Group	A	B	C	D	All	All	All
Price Change in the Peak Rate Period	+6	+12	+18	+24	[-]	[-]	[-]
FEs: Household by Half-Hourly Time Window	Yes	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	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	506,540	326,800	511,700	331,960	1,006,200	1,006,200	1,006,200
Adjusted R^2	0.384	0.397	0.383	0.367	0.308	0.379	0.372

Note: This table shows the results of the regression in Equation (2). The first four columns demonstrate the result for each of the four tariff groups in the peak rate period. The last three columns provide the result of all four tariff groups for each of the three periods. Standard errors in parentheses are clustered at the household and day of experiment levels to correct for serial correlation. The ranges in brackets are the 95% confidence intervals; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

The measured ATEs for the peak rate period re-confirm the finding provided in Prest (2020).[22] The table clearly shows that within-household aggregate demand for electricity during the peak rate period declined, with a significance level of 0.01, due to the deployment of TOU pricing. However, based on the point estimates for the four tariff groups, it is unclear whether an incremental change in peak-rate-period price increase induces a statistically meaningful additional change in household electricity consumption or not.

To quantify how residential consumers responded to the TOU program in off-peak hours close to the peak rate period, I also estimate ATEs in periods of two hours before and after the peak rate period (i.e., in pre- and post-peak periods). Interestingly, the table also demonstrates that in the pre- and post-peak periods, the implementation of the TOU tariff structures resulted in reductions in household electricity consumption, which are statistically different from zero, even though TOU prices were lower than the flat rate of 14.1 cents per kWh.[23] The reductions in both periods surrounding the peak hours suggest that the impact of the price increases in the peak rate period overtook the impact of the price drops in each off-peak period. Therefore, in the following empirical analysis, I will focus on linking household electricity consumption in the pre- and post-peak periods with the price increases in the peak rate period, instead of the price decreases in those off-peak periods.

3.2 Breakdown of Household Responses to Time-Of-Use Electricity Pricing

3.2.1 Breakdown of Household Responses in and near the Peak Rate Period

Figure 5 indicates the limitations of focusing on aggregate electricity consumption, as many studies have been doing. The figure clearly shows that aggregate household electricity consumption increases as the weather becomes colder in Ireland. Intuitively, the negative correlation between them can be mainly attributable to for-heating electricity consumption, which strongly depends on outdoor temperatures. It is a fact that aggregate residential electricity consumption also includes another type of electricity consumption: electricity consumption that is irrelevant to temperature variation, such as consumption for lighting. Those two broad categories of electricity consumption could react differently to TOU electricity pricing. Electricity consumption for heating can be transferred to a different time of the day (e.g., from 6 p.m. to 4 p.m. to avoid a higher unit price under the TOU tariff structures). On the other hand, electricity consumption for lighting is time sensitive. Due to the difference in the costs of relocating or changing electricity consumption, it is possible that the two channels of household electricity consumption respond to TOU electricity pricing in different ways. Therefore, using aggregate electricity consumption to examine households' responses to the time-varying price scheme enables me to access only the aggregated response.

Considering the discussion above, I decompose household electricity consumption into two broad categories—non-temp.-control-driven and temp.-control-driven electricity consumption—and examine how each category of

[22] See Figure 6 in Prest (2020).

[23] Even insignificant point estimates (i.e., point estimates for Tariff Groups C and D in the pre-peak interval and Tariff Group C in the post-peak interval) have negative values.

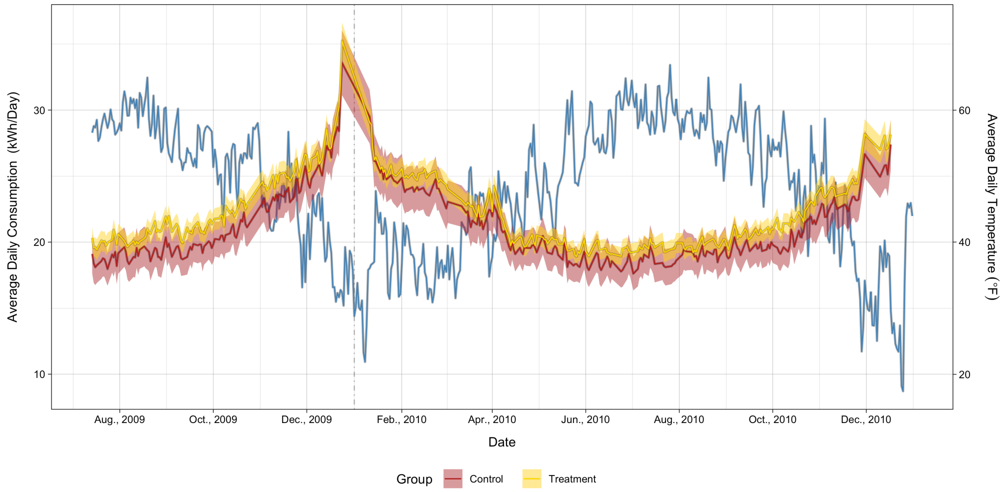

Figure 5: Average Daily Electricity Consumption

Note: The figure depicts, for households that exploit non-electric energy sources for their space and water heating, not only the average daily electricity consumption with 95% confidence intervals for each group (red and yellow lines) but also the mean daily temperature (blue line). From this figure, it is apparent that household daily electricity consumption is negatively correlated with the average daily temperature. In other words, in Ireland, outdoor temperatures are a crucial driver of within-household electricity consumption.

electricity consumption responds to the introduction of the TOU tariff structures. The temperature-control-related electricity consumption here means using electricity to satisfy home heating needs (e.g., to warm up space or water). So, the use of electricity for heating strictly depends on each day's weather conditions, especially temperatures. Naturally, the non-temperature-control-associated electricity consumption makes up the rest.

I exploit daily Heating Degree Days (HDDs), which imply overall heating needs on a given day, to isolate the temperature-control-driven consumption from aggregate household electricity consumption. Because only aggregate metering data is available from the CER experiment dataset, there is no clue allowing me to classify household electricity consumption into two distinct categories in the dataset. To address this challenge, I presume that the portion of household electricity consumption that fluctuates according to daily HDDs is temperature-control-driven electricity consumption. Therefore, the electricity consumption for temperature-control use is additional consumption that appears only on days with non-zero daily HDDs due to household heating needs.

To break down household responses to the TOU program around the peak rate period, I exploit the following DID-style spline regression model:[24]:

$$\begin{aligned} kWh_{ith} \; = \; & \beta_1 HDD_t \; + \; \beta_2 HDD_t^{*} \\ & + \; \big(\beta_3 \; + \; \beta_4 HDD_t \; + \; \beta_5 HDD_t^{*}\big)\mathbb{1}[\text{Treatment}]_i \\ & + \; \big(\beta_6 \; + \; \beta_7 HDD_t \; + \; \beta_8 HDD_t^{*}\big)\mathbb{1}[\text{Post}]_t \\ & + \; \big(\beta_9 \; + \; \beta_{10} HDD_t \; + \; \beta_{11} HDD_t^{*}\big)\mathbb{1}[\text{Treatment \& Post}]_{it} \; + \; \kappa_{dw} \; + \; \epsilon_{ith} \end{aligned} \tag{3}$$

[24]The control group's less percentage changes on freezing days, which are illustrated in Figure (3) substantiate the use of the DID-style spline regression model in 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. In this model, the full set of fixed effects in (2) has been superseded by two indicator variables—the first indicator variable $\mathbb{1}[\text{Treatment}]_i$ has the value of 1 if household i is assigned to the treatment group, and the second indicator variable $\mathbb{1}[\text{Post}]_t$ equals 1 when the day t is in the treatment period. Although using the fixed effects as in (2) does not affect the treatment effects of interests, which is expected given the randomization, replacing them with the indicator variables allows for the interpretation of the average consumption by the treatment group to be more straightforward.[25] The model also includes interaction terms between HDD-relevant terms and those indicator variables. In the econometric model, HDD_t means the daily heating degree days on the day t. And HDD_t^*, which is required to introduce nonlinearity in HDD-associated response to TOU pricing, is mathematically defined as follows:

$$HDD_t^* \; = \; (HDD_t - Knot) \; \times \; \mathbb{1}[HDD_t > Knot], \tag{4}$$

where $Knot$ is a reference value at which the slope of the predicted line starts to change. For $Knot$, I utilize the value of ten in the following regression analysis because the median values of daily HDDs in the baseline and treatment periods are ten. The term κ_{dw} is day-of-week-by-half-hourly-time-window fixed effects.

The primary coefficients of interest in (3) are β_9, β_{10}, and β_{11}. The three coefficients show how much electricity consumption changes in the households assigned to the treatment group changed after implementing the TOU program compared to those in the control group. To be specific, β_9 demonstrates the change in residential electricity consumption for non-temperature-control use. Both β_{10} and β_{11} collectively represent the change in the amount of electricity consumed to meet household heating needs at given daily HDDs.

Using the point estimates of the three coefficients of interest, I graphically summarize the predicted change in each of the two channels of electricity consumption in Figure 6. Regarding the change in electricity consumption for non-temperature-control use, the table and figure clearly show that the treated households significantly reduced their consumption when subject to peak-hour prices (i.e., in the peak rate period). Their non-temperature-control-driven electricity consumption also decreased in the pre- and post-peak periods, albeit noisy and relatively smaller in magnitude than the peak-hour changes.

The change in temperature-control-associated electricity consumption occurred as well in all three two-hour periods, but its evolving pattern over daily HDDs was quite different in each period. Specifically, the impact of TOU pricing on residential electricity consumption for heating was U-shaped in the peak rate period. In contrast, in the hours before and after the peak period, the TOU intervention altered the electricity use for heating only on the coldest days (i.e., only when daily HDDs were sufficiently large). In other words, from the figure, it is evident that the change originating from temperature-control-related electricity consumption was a nonlinear function of daily HDDs in all three periods.

Specification (3) is also utilized to examine, for the peak rate period, the relationship between the degree

[25] Added indicator variables instead of various fixed effects also enables an easier graphical summary of the regression results.

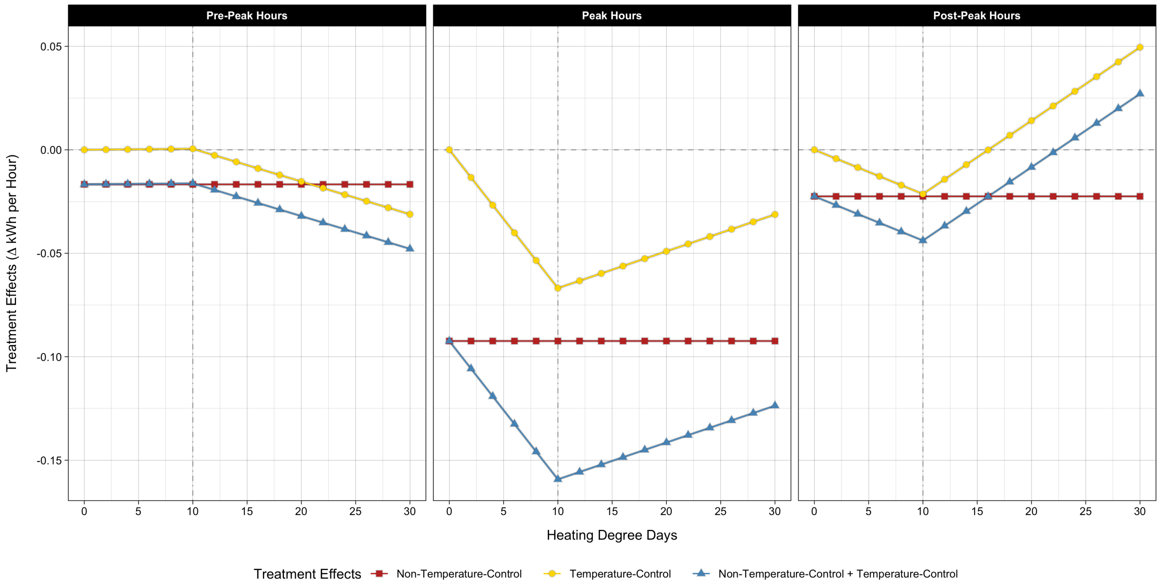

Figure 6: Breakdown of Hourly Average Treatment Effects

Note: This figure is a graphical summary of the regression results. The order of panes corresponds to that of columns. As clearly illustrated, each two-hour interval shows distinct evolving patterns of two broad categories of household electricity consumption. The changes in non-temperature-control-driven household electricity consumption are straight lines because they are independent of outdoor temperature variation. On the other hand, the changes in temperature-control-associated residential electricity consumption are a nonlinear function of daily HDDs.

of a price increase in that period and the change in electricity consumption. On the whole, the reduction stemming from electricity demand for non-temperature-control use tends to be proportional to the size of price growth in peak hours, even though the point estimate for Tariff Group C is an exception. Therefore, the marginally diminishing effects of TOU pricing, discussed in Prest (2020), seem not to be championed by my point estimates. To be specific, while the aggregate electricity consumption during the peak rate period does not sensibly respond to incremental changes in the peak-hour price, the amount of electricity used for non-temperature-control purposes in the peak rate period does respond meaningfully to the marginal changes in the peak price. And the two estimates associated with temperature-control-driven electricity consumption (i.e., $\hat{\beta}_{10}$ and $\hat{\beta}_{11}$) are statistically significant only for the case of the smallest price increase.[26]

Altogether, those results imply two interesting points. First, the two distinct types of electricity consumption showed widely different responses to TOU prices in all three periods of two hours. Second, the measured reductions in non-temperature-control-related electricity consumption seem highly sensitive to the magnitude of a price increase in the peak rate period. Inspired by those implications, I formulate the resulting variations in household electricity consumption as a linear function of the magnitude of a rate change in peak-demand hours in the following section.

[26]In case of Tariff Group D, only $\hat{\beta}_{11}$ is statistically significant.

3.2.2 Household Responses as a Linear Function of Price Changes

To fully understand how residential consumers adjust their consumption behavior in response to price changes under the TOU program, it is necessary to explicitly examine the relationship between the size of the price changes and the change in each of the two distinct categories of household electricity consumption for each of the three periods (i.e., the pre-peak, peak, and post-peak periods). In other words, quantifying the impact of the marginal price change on residential electricity consumption will help evaluate the role of the intraday price variation under TOU electricity pricing. In the analysis, I utilize the magnitude of the price changes, from the flat rate, in the peak rate period for all three periods. There are two reasons why I exploit the price increases in the peak rate period rather than those in the corresponding period. One reason is that in the pre- and post-peak periods, the estimated changes in household electricity consumption do not show any apparent correlation with the price decreases in the corresponding periods.[27] The other reason is that the price changes in the peak rate period well encapsulate two different price incentives under TOU pricing in off-peak hours, price incentives for load-shedding and load-shifting.[28] Using the following econometric model, I quantitatively determine the relationship:

$$
\begin{aligned}
kWh_{ith} \;=\; & \beta_1 HDD_t \;+\; \beta_2 HDD_t^{*} \\
& +\; \left(\beta_3 \;+\; \beta_4 HDD_t \;+\; \beta_5 HDD_t^{*}\right) \mathbb{1}[\text{Treatment}]_i \\
& +\; \left(\beta_6 \;+\; \beta_7 HDD_t \;+\; \beta_8 HDD_t^{*}\right) \mathbb{1}[\text{Treatment}]_i \Delta PC_i \\
& +\; \left(\beta_9 \;+\; \beta_{10} HDD_t \;+\; \beta_{11} HDD_t^{*}\right) \mathbb{1}[\text{Post}]_t \\
& +\; \left(\beta_{12} \;+\; \beta_{13} HDD_t \;+\; \beta_{14} HDD_t^{*}\right) \mathbb{1}[\text{Treatment \& Post}]_{it} \\
& +\; \left(\beta_{15} \;+\; \beta_{16} HDD_t \;+\; \beta_{17} HDD_t^{*}\right) \mathbb{1}[\text{Treatment \& Post}]_i \Delta PC_i \;+\; \kappa_{dw} \;+\; \epsilon_{ith}
\end{aligned}
\tag{5}
$$

The model is the same with (3) except for interaction terms between treatment-status-relevant indicator variables (i.e., $\mathbb{1}[\text{Treatment}]_i$ and $\mathbb{1}[\text{Treatment \& Post}]_{it}$) and ΔPC_i, where ΔPC_i is the difference between the peak-hour prices in the treatment period and the flat rate in the baseline period. The coefficients of the second interaction term (i.e., β_{15}, β_{16}, and β_{17}) capture the impacts of deploying TOU tariffs on household electricity consumption as a linear function of the degree of a peak-demand-hour price change.

The estimates of the six coefficients of interest (i.e., from β_{12} to β_{17}) are summarized graphically in Figure 7, which is extensively exploited throughout this paper. And this figure, showing the estimated treatment effects for the two consumption channels and the sum of the treatment effects in each of the three intervals, re-confirms the finding of peak-rate-period price increases' diminishing returns in Prest (2020).

In the peak rate period, the reduction in non-temperature-control-associated electricity consumption in-

[27] As discussed in the previous section, the price increases in the peak rate period clearly drive the changes in the two types of electricity consumption in the same period.

[28] Before and after the peak period, the two price incentives are proportional to the magnitude of the price increases in the peak period.

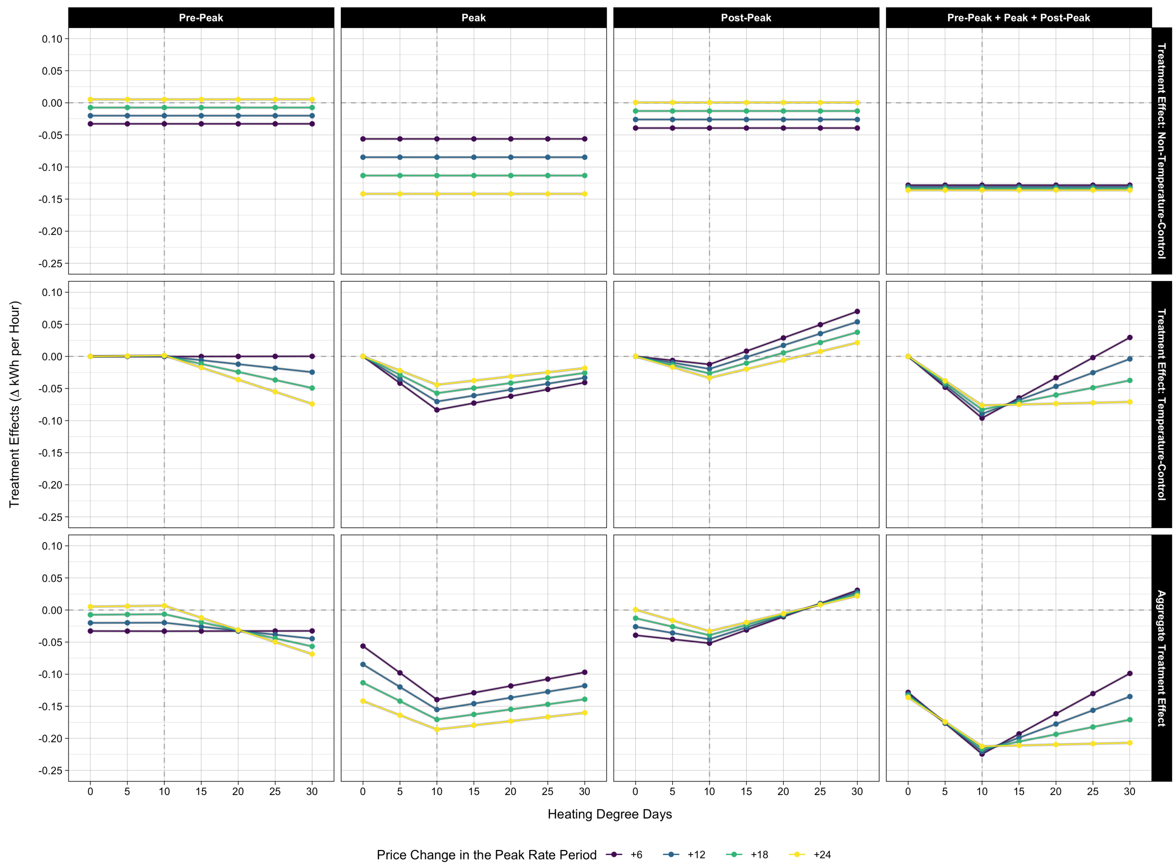

Figure 7: Treatment Effects as a Linear Function of Peak-hour Price Changes

Note: This figure depicts, for four different price changes in the peak rate period, estimated treatment effects as a linear function of price changes. The first row in the figure shows the treatment effects on non-temperature-control-driven household electricity consumption. The treatment effects on temperature-control-related residential electricity consumption are illustrated in the second row. The aggregate effects are presented in the last row. The first three columns correspond to the three two-hour periods (i.e., pre-peak, peak, and post-peak periods). The fourth column demonstrates the total changes in the three periods.

creased as the magnitude of a peak-hour price increase grew (see the panel in the first row of the second column of Figure 7). On the contrary, at given daily HDDs, the reduction in temperature-control-related electricity consumption weakly moved towards zero as the size of a peak-demand-hour tariff escalation increased (see the panel in the second row of the second column of Figure 7). As well illustrated in the panel in the third row of the second column of Figure 7, for a given value of daily HDDs, the differences in treatment effect across the level of price growth are seemingly dampened when the estimated treatment effects from two distinct categories of electricity consumption are aggregated due to the opposite response to peak-hour price increases in the two consumption categories.[29] Indeed, this empirical result is consistent with the finding discussed in the paper that a higher price results in a larger diminution in electricity demand, while additional gains diminish in the peak interval.

In the two-hour interval before the peak rate period, the two types of residential electricity consumption continue to respond differently to the peak price for given daily HDDs, but the pattern is now switched. The pre-peak period exhibits a more significant reduction in non-temperature-control-driven electricity consumption for a more minor change in peak-hour price (see the panel in the first row of the first column of Figure 7). By contrast, the larger the magnitude of a peak-rate-period price change, the wider the diminution in temperature-control-related electricity consumption during the pre-peak period (see the panel in the second row of the first column of Figure 7). For the same reason as in the peak period, the aggregate treatment effects of the TOU tariffs described in the last row of the first column of Figure 7 are seemingly less sensitive to peak-hour prices. Note that regarding electricity consumption for heating during the pre-peak period, TOU electricity pricing played a role only when household heating needs were sufficiently high.

Irish residential consumers adjusted their electricity consumption behavior during the post-peak period as well. As in the pre-peak period, consumption changes stemming from non-temperature-control-related electricity use increased as the size of a peak-demand-hour rate change diminished (see the panel in the first row of the third column of Figure 7). The TOU-price-induced change in temperature-control-driven electricity consumption evolved over daily HDDs somewhat complicatedly. Though depending on the magnitude of a peak-hour price increase, TOU tariffs reduced household electricity consumption for heating on Ireland's typical winter days in that period. Interestingly, the CER TOU program provoked additional heating-related consumption during the post-peak period on extremely cold days in Ireland. In addition, as the level of peak-demand-hour price alteration grew, the profile of measured treatment effect for temperature-control-associated consumption moved downward. Consequently, a higher price increase in the peak rate period resulted in a more significant reduction in electricity consumption for heating when heating demands were lower, while a smaller addition to electricity consumption for heating on cold winter days (see the panel in the second row of the third column of Figure 7). Altogether, as shown in the last row of the third column of Figure 7, the aggregate treatment effects of the TOU program in the post-peak period are superficially moderated because of households' opposite responses to peak-demand-hour price increases in the two distinct channels of electricity consumption.

In summary, under TOU electricity pricing, the degree of a price change in peak-demand hours, not just its existence, still matters to residential consumers' electricity consumption. The empirical results above suggest that the opposite directional changes in the two channels of electricity consumption make Irish households appear insensitive to the time-varying price structure. In other words, their high sensitivity to TOU prices is revealed only when their electricity consumption is disaggregated. Together with the empirical findings in previous sections, the results imply that three simultaneously interacting factors govern the dynamics of residential electricity consumption under TOU pricing: the timing when electricity is consumed, daily HDDs, and the magnitude of price increase in the peak rate period.

[29] The last row of Figure 7 shows the sum of the first and second rows.

3.3 Dynamics of Household Electricity Consumption under TOU Pricing

3.3.1 Mechanism: Load-shedding vs. Load-shifting

Examining participating households' electricity consumption, following a time sequence from the pre-peak to the post-peak period, facilitates a complete understanding of how they adapted to the TOU tariff structures in the CER experiment. Intuitively, residential consumers can respond to TOU tariffs by conserving their electricity consumption during the peak-demand hours, leading to an overall reduction in their demand for electricity. Instead of reducing their electricity consumption, they can shift it to off-peak hours so as not to be subject to the peak rate as much as possible. In this case, the level of their net electricity consumption in a day is maintained. Of course, those two ways of responding to time-varying price structures can co-occur. Because those two ways reshape load curves not only in the peak rate period but also in the hours surrounding that period, it will be natural to examine the impact of the TOU program on household electricity consumption from a time-moving perspective in order to grasp the whole dynamics of households' behavioral changes. In the following paragraphs, I will provide interpretations of the changes in households' consumption behavior, which are observed in my empirical analysis.

Regarding residential electricity demand for non-temperature-control uses, the leading reaction of the treated households to the TOU tariffs was to reduce their consumption in and near the peak rate period. According to my regression results summarized in Figure 7, in the peak rate period, the reduction in non-temperature-control-related electricity consumption increased as the magnitude of the price change in that period under the TOU program grew. Non-temperature-control-driven electricity consumption in the pre- and post-peak periods showed a weak but opposite variation—i.e., the reduction originating from households' non-for-heating consumption moved towards zero as the degree of the price increase in the peak rate period became larger. In the case of Tariff Group A, although there was almost zero price variation relative to the flat rate (i.e., only 0.1 cents per kWh) in the pre- and post-peak periods, the amount of the diminution in non-temperature-control-related electricity consumption for that group was nearly the same in all three periods. Meanwhile, despite more sizable price decreases, the remaining tariff groups also conserved, or at least sustained, their consumption for non-temperature-control uses in both surrounding periods. In other words, my empirical results reveal that reductions in households' non-for-heating electricity consumption spilled over into non-peak periods (i.e., the pre- and post-peak periods).

A remarkable point with respect to the spillovers to non-peak hours, suggesting households' behavioral changes related to non-temperature-control-driven electricity consumption in the pre- and post-peak periods, is that they seemed to relocate a part of their not-for-heating electricity consumption during peak hours to those two periods. As described in Figure 1, there were price drops in the hours before and after the peak rate period. Furthermore, for marginal electricity consumption, because the tariff group that paid the highest price in the peak rate period (i.e., Tariff Group D) paid the lowest price in the surrounding hours, the households in that group were more incentivized to move their peak-hour electricity consumption to off-peak hours. Hence, the phenomenon that the reduction in not-for-heating electricity consumption in the surrounding periods declined as the magnitude of the peak-rate-period price change increased is well explained by combining the load-shedding with the load-shifting, which was motivated by the monetary incentive from the price differences between the peak and off-peak periods. As shown in Figure 7, the relocation-associated consumption change, in general, did not fully outweigh the conservation-relevant one in both periods.

Taken together, with respect to non-temperature-control-driven electricity consumption, the households assigned to the treatment group responded to the TOU program via load-shedding as primary and load-shifting as secondary reactions. Interestingly, the total non-temperature-control-relevant reduction in and near the peak rate period, which is depicted in the fourth column of the first row in Figure 7, did not vary with the level of a peak-hour price increase. This outcome might reflect households' limited capability not only to identify possible sources of reducing their electricity consumption but also to realize lower consumption from the sources.

With respect to temperature-control-related household electricity consumption, Figure 7 depicts that the program caused a reduction in for-heating electricity use during the peak rate period, especially around typical values of daily HDDs during winter in Ireland. Interestingly, although statistically insignificant, the smaller the magnitude of the peak-demand-hour price change increase, the larger the induced reduction in temperature-control-related consumption in the peak period. That is, the change in for-heating electricity consumption seems to violate the law of demand. As discussed above, the households assigned to Tariff Group D had the highest incentive to relocate their peak-hour electricity consumption to non-peak hours surrounding the peak-demand hours due to the largest across-period price difference. Therefore, the reduction in electricity consumption for heating in the pre-peak period, which occurred only on days with heavy heating needs, cannot be explained as a consequence of either the price decrease in that period or load-shifting. In other words, regarding temperature-control-driven household electricity consumption, as did in the peak rate period, the price signals did not function well in the pre-peak period. In the post-peak period, high daily HDDs incurred additional electricity consumption for heating after introducing TOU tariffs. The degree of the additional consumption, however, also cannot be justified by the price signals for the same reasons as in the pre-peak period.[30] And the amount of the additional consumption was generally not large enough to fully offset, for given heating needs in a day, the reduction in the preceding periods. In Section 3.3.2, I will discuss a possible explanation for the consumption behavior not backed by the price signals.

3.3.2 Household Electricity Consumption for Heating in a Time Line

From Figure 7, examining the curves that illustrate the change in temperature-control-associated electricity consumption for three consecutive periods simultaneously, but taking account of their time sequence, suggests

[30] The estimated changes in temperature-control-related electricity consumption with respect to peak-demand-hour price variation for the peak and post-peak periods, presented in Figure 7, seem rather to imply that the degree of load-shifting diminished as the financial incentive, measured by the price difference between the two periods, increased.

a significant implication of the effectiveness of the TOU prices in the peak rate period. According to the figure, as the degree of peak-hour price escalation increased, the temperature-control-related consumption reduction in the pre-peak period expanded, while those in the peak period decreased gradually. Altogether, it is likely that a larger pre-adjustment leads to a smaller reduction in electricity demand for heating during peak-demand hours, which in turn seems to result in limited additional consumption during the following post-peak period. Compared to the case that a household does not reduce for-heating electricity consumption during the pre-peak period, consuming more for-heating electricity during peak hours seems necessary to prevent indoor temperatures from falling too much or persisting at a low level when the household significantly reduces its temperature-control-driven consumption during the pre-peak period.[31] In addition, the household will have less incentive to increase its electricity consumption for heating during post-peak hours since its room temperatures will be higher than if it were to reduce its electricity consumption for heating during peak hours considerably. In light of the fact that TOU tariffs are intended to conserve electricity consumption during peak-demand hours, it is reasonable to conclude that a lower reduction in peak hours due to a too large pre-adjustment results in a deterioration in the performance of the TOU tariffs.

As discussed in detail, under the TOU program, households' adjustments to their behavior for temperature-control-driven electricity consumption during the pre-peak hours seem to determine the degree of a reduction in that use of electricity during the following period (i.e., during the peak rate period) in lieu of price signals. In Figure 7, the gap in the temperature-control-related treatment effect at given daily HDDs between the lowest and the highest peak-hour rate changes, therefore, might be understood as potentially attainable gains when the pre-adjustments are suppressed. This explanation motivates the necessity of adopting home automation technologies, like Programmable Communicating Thermostats (PCTs), to restrict such adjustments only to the peak rate period. Considering the fact that households generally set a target temperature instead of micromanaging their heating devices according to ever-changing outdoor temperatures, PCTs with recommended default settings for temperature-control-associated use of electricity are highly likely to contribute to minimizing their behavioral changes prior to the peak rate period.[32] Moreover, the additional gains realized by utilizing the automated instruments provide legitimacy for the ongoing SEAI-offering Home Energy Grants, in which heating controls are an essential part.[33]

[31] This interpretation is in line with the concept "discomfort" in Blonz et al. (2021). See Section 3.4 in the paper.

[32] Fowlie et al. (2021) examines default effects in a randomized controlled trial, in which the participants assigned to the control group defaulted into a residential electricity pricing program. Default effects have been studied in a range of settings, such as organ donation (Johnson and Goldstein, 2003; Abadie and Gay, 2006), car insurance (Johnson et al., 1993), and participation in retirement savings plans (Samuelson and Zeckhauser, 1988; Madrian and Shea, 2001; Choi et al., 2019).

[33] Sustainable Energy Authority of Ireland (SEAI) is Ireland's national sustainable energy authority whose goal is to promote and assist the development of sustainable energy in Ireland. Detailed information about Home Energy Grants is available at https://www.seai.ie/grants/research-funding/.

4 An Alternative Electricity Pricing

4.1 Household Consumption Behavior over Daily Heating Degree Days

My empirical results obviously illustrate that the effectiveness of TOU tariffs, as measured by the amount of an induced reduction in household electricity consumption, nonlinearly varies with daily HDDs. As discussed, the alteration in electricity consumption caused by the deployment of TOU electricity pricing consists of two elements: the change in non-temperature-control-driven electricity consumption and that in temperature-control-driven electricity consumption. By definition, the change originating from non-temperature-control-related electricity consumption is independent of ever-changing weather conditions, including daily HDDs. Hence, the nonlinearity in the effectiveness of the TOU tariff structures, as illustrated in Figure 7, is utterly attributable to the other type of electricity consumption, that for heating.

The nonlinear relationship between the amount of change in temperature-control-associated electricity consumption and daily HDDs indicates an interesting characteristic of TOU pricing: the day-varying effect of TOU pricing on residential electricity consumption. Daily HDDs, one of the critical determinants of temperature-control-relevant electricity consumption, fluctuate day by day. Therefore, it is intuitive that in response to daily changing household heating needs, the TOU-price-induced change in electricity consumption for heating also alters every day.

The day-varying effectiveness of TOU electricity pricing suggests a significant implication in connection with Real-Time Pricing (RTP), a more granular time-varying electricity tariff structure.[34] Contrary to TOU pricing, rates typically change hourly under RTP. So compared to TOU pricing, RTP has an advantage in reflecting generation costs contemporaneously. In other words, RTP imposes a higher price in the situation that electricity demand is high, followed by high generation costs, to curb household electricity consumption. Economists, therefore, often advocate RTP over TOU pricing.

Because of the reduction in temperature-control-driven electricity consumption that covaries with daily HDDs, TOU electricity pricing can somewhat emulate the favorable feature of RTP on relatively warm winter days in Ireland—roughly speaking, on days when the value of daily HDDs is below ten. As evidently illustrated in Figure 5, households' heating needs drive the demand for electricity in Irish households. So, a more significant diminution in household electricity consumption is required on cold winter days to relieve the burden on the power grid. According to Figure 7, for example, for the households in Tariff Group A, the reduction in heating-associated electricity consumption in the peak rate period on warm winter days (i.e., on days when the value of daily HDDs fell between zero and ten), whose amount was more than half of the aggregated reduction in household electricity consumption under the TOU program at its maximum, expanded as households' heating needs became larger. This empirical finding means that comparing two warm winter days in Ireland, which have different values of daily HDDs, despite no across-day price variation under the price scheme, TOU electric-

[34] Harding and Sexton (2017) provides a detailed description of various kinds of time-varying electricity tariff structures.

ity pricing induces a larger reduction in household electricity consumption during peak hours on the day with higher HDDs (i.e., on the day demonstrating higher generation costs due to more significant electricity demand). Consequently, in that case, the additional gains obtained by switching to RTP might not be as substantial as economists have expected. The excellent feature of TOU electricity pricing, however, gradually disappeared as daily HDDs grew above the value of ten, even though a more considerable reduction in household electricity consumption is required to ease the burden on the power grid.

4.2 TOU Pricing with Additional Dynamics over Daily Heating Degree Days

The U-shaped curve of peak-demand-hour reduction in temperature-control-related electricity consumption is not a desirable feature of TOU electricity pricing. The fundamental intention of the time-varying tariff scheme is to reshape load profiles, especially in the peak rate period, in order to avoid excessive investment in power generation capacity. So a higher amount of reduction in electricity consumption for heating on freezing days (i.e., on days when the power grid is most burdened) serves the purpose of the price scheme. In light of that, the U-shaped evolving pattern over daily HDDs is unattractive because on days with high heating needs, TOU electricity pricing induces even less reduction in for-heating-relevant household electricity consumption.

An alternative electricity pricing scheme, a TOU-like tariff structure with additional flexibility in price variations across daily HDDs, could address the disadvantage of typical TOU pricing revealed from my analysis (i.e., less effectiveness on days with very low temperatures). My empirical findings illustrate two important points with respect to the relationship between TOU-tariff-induced changes in household electricity consumption and price increases during the peak rate period. First, the reduction stemming from non-temperature-control-associated electricity consumption becomes larger as the magnitude of a price escalation in the peak period increases. Second, the gains obtained by marginally raising the peak-hour electricity price (i.e., an additional reduction in non-temperature-control-relevant electricity consumption) exceed the losses from such a marginal increase (i.e., a fewer reduction in temperature-control-driven electricity consumption).[35] Those two points collectively imply that scaling up the size of a rate change in the peak rate period as daily HDDs rise enables achieving a more considerable TOU-price-induced aggregate reduction in residential electricity consumption.

Figure 8 depicts an alternative price scheme and additional gains from it. Under the price scheme proposed in the upper part of the figure, the peak-demand-hour price jumps as household heating needs become serious. To be specific, prior to the value of daily HDDs that typical TOU pricing becomes ineffective, the magnitude of peak-rate-period price change is evenly six cents per kWh. After that point, every time daily HDDs rise by five, the degree of peak-demand-hour price change increases by six cents per kWh.

The lower part of Figure 8 shows additional gains from the alternative pricing scheme, which are shaded with distinct colors for each six-cent escalation in peak-rate-period price. The five U-shaped profiles over daily

[35] See the three panels in the second column of Figure 7.

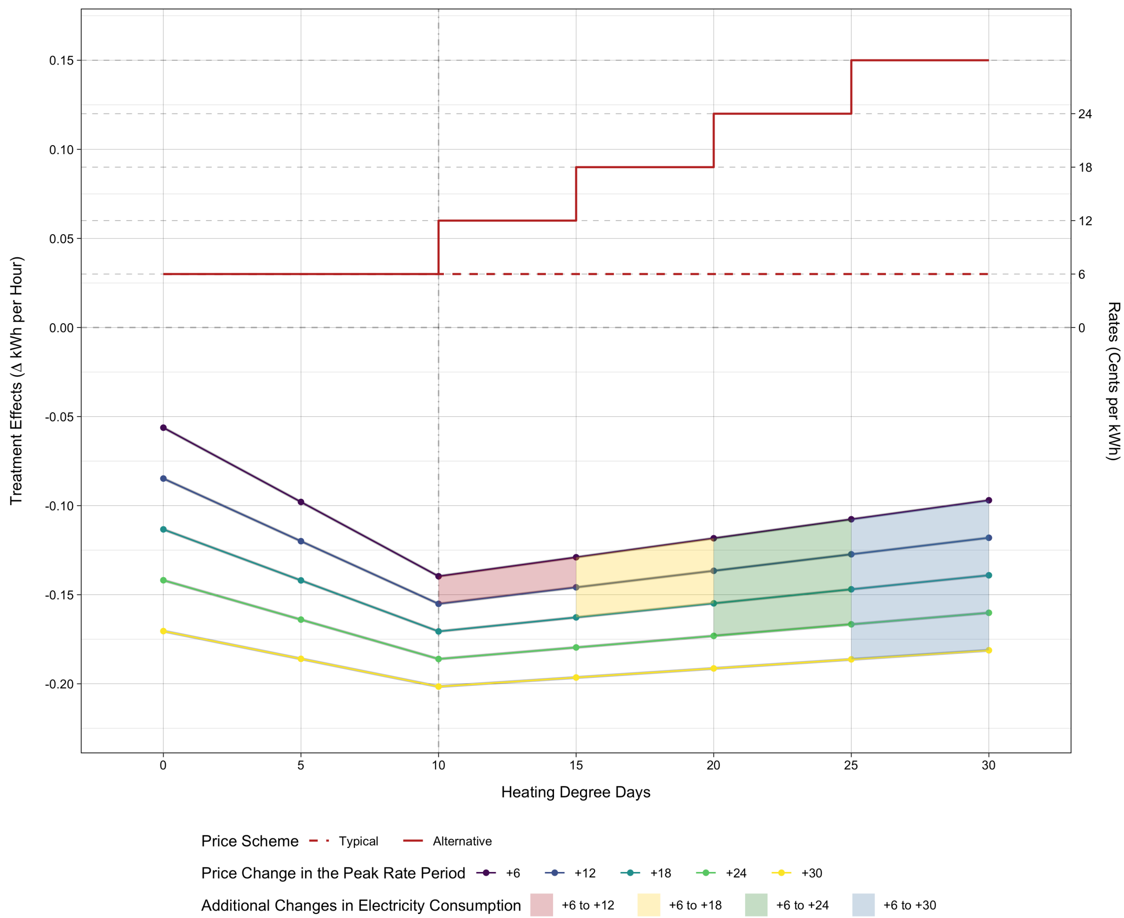

Figure 8: Additional Gains from an Alternative Electricity Pricing Scheme

Note: This figure illustrates two different price schemes. Under a typical TOU electricity pricing scheme, the rate in the peak rate period is 6 cents per kWh regardless of daily HDDs. On the contrary, under an alternative tariff structure that is TOU-style but has extra flexibility across daily HDDs, the peak-hour price escalates as household heating needs grow. The shaded areas depict additional gains obtained by adopting the redesigned pricing scheme, which are mainly attributable to more significant reductions in non-temperature-control-driven household electricity consumption.

HDDs, indicating the predicted reductions in household electricity consumption for five different price changes in the peak rate period, are drawn by utilizing the point estimates. As illustrated in the figure, compared to the case in which the size of peak-hour price growth is fixed at six cents for all values of daily HDDs, the alternative price scheme can induce more significant reductions in household electricity consumption according to increasing household heating needs by synchronizing price increases in the peak rate period with daily HDDs. In other words, the weakness of typical TOU pricing can be alleviated under the proposed price structure.

The alternative price scheme is well in line with the key finding in Schittekatte et al. (2022). According to this recent paper, TOU rates complemented with Critical Peak Pricing (CPP) work well for reflecting spot-price-providing within-day load-shifting incentives. Considering that CPP introduces dramatic but short-lived price escalations when generating costs exceed a certain threshold infrequently, a very high peak price linked with exceptionally large daily HDDs in Ireland under the proposed alternative price scheme is consonant with CPP events with which TOU prices are complemented as suggested in the paper.

In addition, this proposed price structure is better than the typical TOU tariff structure with a higher fixed peak-demand-hour price. For example, Tariff Group D reduces household electricity consumption as much as the alternative price scheme on extremely cold days. However, compared to Tariff Group D, households under the proposed price structure can consume more electricity on warm days on which the power grid still has enough spare capacity to meet higher electricity demand.

5 Conclusion

The primary aim of various types of time-varying electricity pricing is to reshape load curves, especially around the peak-demand hours. Under the dynamic pricing of electricity, prices—more precisely, price variations—, which reflect instantaneous generation costs, are utilized to incentivize consumers to change their consumption behavior. Therefore, their responsiveness to the price changes in the tariff structures determines whether the time-varying electricity prices, including TOU pricing, will work as intended. In this paper, I quantify how sensitively households adjust their electricity consumption in response to TOU prices in and near the peak rate period. The results from my empirical analysis reveal two interesting points: household electricity consumption, consisting of two categories of electricity use—non-temperature-control-driven and temperature-control-driven consumption—, 1) sensitively responded to the magnitude of the price change in the peak rate period, and 2) also depended on daily heating degree days as well as the point electricity was consumed in time for a given rate change. In other words, my empirical analysis discloses the multidimensional dynamics of households' responses to the TOU tariffs.

Those findings provide important policy implications for TOU electricity pricing. First, along with residential consumers' high price sensitivity, the nonlinearity in their responses to daily heating needs proposes an alternative pricing scheme: TOU pricing with additional flexibility induced by synchronizing the magnitude of the peak-demand-hour price jump with daily heating degree days. Second, taking a close look at the relationship between the size of the peak-hour price increase and the changes in electricity consumption for temperature-control uses in chronological order emphasizes the importance of adopting home automation technologies, like Programmable Communicating Thermostats (PCTs), to improve the performance of TOU pricing.

My empirical findings and the policy implications derived from them ultimately indicate that an integrated understanding of the multidimensional dynamics of households' responses to TOU electricity pricing is required to make the price structure function with its full potential as a demand management tool. Furthermore, even for stakeholders in the electricity market, such as power generators, investors, regulators, and policymakers, comprehending how electricity consumption reacts to the time-varying pricing is critical because consumers' behavioral changes are an important piece of information in their decision makings.

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