Job Market Paper

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Contents

List of Tables

List of Figures

Abstract

The existing literature has found that while Time-of-Use (TOU) electricity pricing causes reductions in aggregate household electricity consumption during peak-demand hours, the magnitude of these reductions is largely insensitive to incremental changes in the peak period price. In this paper, I re-examine the impact of TOU rates on residential electricity consumption with a different approach. Specifically, I decompose aggregate household electricity consumption into two different channels of consumption: consumption for non-temperature-control and temperature-control uses. I determine TOU-price-induced changes in both channels of consumption by applying Difference-In-Differences-style (DID-style) spline regression specifications using 30-minute interval metering data collected from an experiment in Ireland. My empirical results demonstrate that residential consumers are, in fact, quite sensitive to incremental changes in the peak-demand-hour price under the TOU tariff structures. However, this sensitivity is masked due to the opposite directional changes in the two channels of electricity consumption—i.e., during the peak hours, non-temperature-control-driven consumption falls as the peak price increases, while temperature-control-driven consumption actually increases as the peak price grows. Moreover, my analysis reveals that the two channels of household electricity consumption evolve differently, and nonlinearly, according to daily heating degree days and the point electricity is consumed in time. Those multidimensional dynamics of residential electricity consumption under TOU tariffs suggest that adopting autonomous heating control systems or augmenting additional across-day variations to the price scheme is required to maximize the benefits of TOU electricity pricing.

1 Introduction

Introduction Many energy utilities are shifting customers onto Time-Of-Use (TOU) electricity rate structures, which have become feasible owing to the diffusion of renewable electricity generation capacity and 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, shifting some of the consumption to lower demand hours potentially, when the cost of supplying electricity is far lower, is another intention of the dynamic rates. Ultimately, how effective the time-varying electricity prices are at reducing peak consumption, and shifting consumption across time, depends on how elastic consumers are to the magnitude of the price increase in peak-demand hours and the price decreases in the off-peak hours. In settings where households are unresponsive to within-day price changes, TOU programs may provide only small gains. In contrast, if consumers are very sensitive to the magnitude of the spread between the off-peak and peak electricity prices, that would suggest that additional gains could be achieved by adopting even more dynamic pricing, such as Real-Time Pricing (RTP), where the peak vs.

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

off-peak price spread varies across days. 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-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 the households' 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 utilized for heating 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 broad category by using temperature variations. 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 residential electricity consumption 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 utilize oil and gas as their primary energy source for heating, a sizable amount of electricity is used for heating in those homes. Notably, residential electricity consumption peaks 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 aggregate changes in temperature-control-driven and non-temperature-control-driven consumption 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

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

vary with the magnitude of the peak-period price change.

From my empirical analysis, I find that the households' non-temperature-control-driven electricity consumption was highly responsive to the magnitude of the peak price change. 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 magnitude of the peak price grew. Instead, there is weak evidence demonstrating that the reduction in temperature-control-driven electricity consumption during peaks went towards zero as the peak 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 is precisely the result discussed in Prest (2020).

To explore why the two distinct categories of electricity consumption (i.e., temperature-control-driven and non-temperature-control-driven consumption) respond somewhat differently to the TOU prices during the peak price hours, I examine how both types of consumption change in the off-peak price hours—in particular, the hours leading up to and following the peak rate period (denoted the pre- and post-peak hours, respectively). In the TOU experiment, the households that experienced price increases during the peak hours also experienced decreases in the prices they paid for electricity in the hours surrounding the peak tariff period. Moreover, the higher the peak price the households had to pay, the lower the off-peak prices (i.e., the day and night rates) they had to pay.

My regression analysis shows interesting non-temperature-control-driven consumption changes in the hours leading up to and following the peak rate period, even though not all relevant points estimates are statistically significant. Specifically, the TOU prices appeared to have a spillover effect on households' demand for electricity in the hours surrounding the peak rate period (i.e., in the pre- and post-peak periods): a reduction in their non-temperature-control-driven consumption even under a lower electricity price. In particular, the more considerable the peak price increase, the smaller the reduction in non-temperature-control-driven electricity consumption during non-peak hours. Furthermore, I find only weak evidence suggesting that larger peak price increases, and corresponding more significant off-peak price decreases, caused households to shift some of their non-temperature-control consumption to the hours surrounding the peak hours. Therefore, along with the TOU-price-induced changes in non-temperature-control-driven consumption during peak hours, these findings imply that with respect to households' non-temperature-control-driven consumption, load-shedding was their dominant reaction to the peak rate increases in and near the peak price period.

My empirical analysis indicates that a different pattern emerged for the temperature-control-driven consumption changes in the pre- and post-peak hours, while the TOU tariffs also seemed to have a spillover effect

[4] There were four tariff groups in the CER experiment. Refer to Figure 1.

on it. Although my results for the temperature-control-associated consumption are weak in terms of statistical significance, 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 peak price 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. Furthermore, interestingly, those consumption changes near the peak rate period were observable only when outdoor temperatures were low enough. Altogether, those are not indicative of load-shifting (e.g., pre-heating their space and water prior to the peak rate period). Rather, those findings suggest that the TOU program caused a reduction in household demand for heating across the entire day.

The findings described above could also contribute to the result that households' temperature-control-driven electricity consumption during the peak rate period was largely unresponsive to the magnitude of the peak price increase. For example, if households that experience a high peak price use less electricity for heating in the pre-peak hours, then they may not be as warm going into the peak hours. Consequently, more significant amounts of electricity may be consumed for heating during the peak price period than otherwise would have been absent the reduction in pre-peak heating. Effectively, households' temperature-control-driven electricity usage does appear to be sensitive to the size of the peak rate in that period. However, such responses are mostly seen prior to the peak rate period—and as a result, make the impacts during the peak hours look potentially more muted. In addition, this interpretation of the sequential behavioral changes related to temperature-control-driven consumption in time suggests an important policy implication: under TOU electricity pricing, impeding such pre-adjustment by exploiting an automation instrument, like Programmable Communicating Thermostats (PCTs), enables more reductions during peak hours.

In addition to their responsiveness to TOU prices, in my empirical analysis, the reduction in households' temperature-control-driven electricity consumption during the peak rate period 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 the 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 variations. My empirical results, however, indicate that on days with moderate heating needs, a sizable share of reductions in household electricity consumption stemmed from electricity usage for temperature control during peak hours. Consequently, even though the TOU tariffs do not change across days, the tariffs already induce substantial reductions 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) are likely to be smaller than many economists have thought.[5]

The U-shaped evolving pattern of the reduction in temperature-control-driven electricity consumption over daily HDDs also implies that TOU pricing induces somewhat smaller decreases on days with relatively large heating needs, on which the grid is most burdened, in turn, the most significant diminution in electricity consumption is required. This undesirable quality of TOU electricity pricing, however, can be addressed by adopting a more flexible TOU-style pricing scheme in which household heating needs are integrated as an additional dimension of dynamics. According to my analysis, raising the size of a rate change in the peak-demand hours prevented the reduction driven by temperature-control-related consumption from disappearing. Furthermore, it produces more reduction in non-temperature-control-associated electricity consumption. In light of those findings, introducing an alternative pricing structure in which the magnitude of peak-hour price increases is proportionally coupled to daily HDDs could create additional gains on high-heating-needs days.

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-price-induced demand declines. My results demonstrate that in and near the peak hours, the changes from each of the two channels of electricity consumption sensitively vary according 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 still matter. Moreover, the day-varying performance under TOU prices suggests a vital policy implication: shifting from TOU towards RTP-like pricing can improve the reduction in residential electricity consumption on extremely cold days. In addition, examining the changes in electricity consumption from the two distinct categories of electricity consumption, not just in the peak rate period but in and near the period, enables unlocking the full benefits of TOU electricity pricing through the automation-technology-relevant policy implication.

2 Data

2.1 Description of CER Experiment[6]

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. 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

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

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.[7]

The households who voluntarily opt-in to the experiment were randomly assigned to control and treatment groups.[8] 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 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.[9] 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.[10]

[7] 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.

[8] 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.

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

[10] 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.[11]

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.[12] From this sample, I drop 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.[13] Moreover, among the non-electric-heating households, those with unreliable meter reads are excluded from the sample.[14] This process results in 1,170 households. Table 0 summarizes the assignment distribution of the 1,170 households.

The control and treatment groups in the sample are largely balanced, as shown in Table 1. ~~Such indifferences~~ between the two groups over many observables are consistent with previous studies examining the CER experiment dataset.[15]

[11] 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).

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

[13] 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 5 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.

[14] To be specific, 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 the 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.

[15] To check the balance between the control and treatment groups, Prest (2020) employs a linear probability model, while a probit

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 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 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. As demonstrated in Table 2, the temperature correlations between the Dublin station and stations near densely populated cities are evident. Because of the close correlations, 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 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). Figure 3 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 temperature-control-

model is used in Pon (2017). 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).

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

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

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 5, 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.

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

[18] An important feature also stands out from the figure: the minimum household electricity consumption occurred at around $60° F$. 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.

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.[21] That is, I estimate the ATEs of the dynamic prices on household electricity demand by exploiting the within-household electricity consumption changes across not only rate periods but temperatures.[22]

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:

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

[21] Under three identifying assumptions, applying a DID strategy to measure electricity 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 during the trial, the assumption implies that the pre-treatment-period load profile for the treated households should be very similar to that for the non-treated households. Figure 2, 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 4, which smoothly evolved over the entire experiment period although heavily fluctuated daily, suggests its high reliability as a counterfactual under the assumption. The assumption of common temporal shocks is the second identifying assumption necessary for the plausibility of the identification strategy employed. 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 4 support the assumption required for the DID approach. Third, the stable unit treatment value assumption (SUTVA) must hold too. The SUTVA requires that introducing the 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.

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

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 6 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 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.[23] 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.

The measured ATEs for the peak rate period re-confirm the finding provided in Prest (2020).[24] The table

[23] 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.
[24] See Figure 6 in Prest (2020).

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.[25] 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 4 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 variations, 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-temperature-control-driven and temperature-control-driven electricity consumption—and examine how each category of 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

[25]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.

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:[26]:

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

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. 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.[27] 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.

[26]The control group's less percentage changes on freezing days, which are illustrated in Figure (5) substantiate the use of the DID-style spline regression model in 3.

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

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 provided in Table 4, I graphically summarize the predicted change in each of the two channels of electricity consumption in Figure 7. 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 they were 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 of a price increase in that period and the change in electricity consumption. The by-tariff-group estimates of the coefficients of interest are also presented in Table 4. As shown in the table, 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 (i.e., only for Tariff Group A).[28]

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

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

household electricity consumption as a linear function of the magnitude of a rate change in peak-demand hours in the following section.

3.2.2 Household Responses as a Linear Function of Price Changes

To fully understand how residential consumers adjust their consumption behavior as a set of reactions to the price changes under the TOU program, it is necessary to explicitly examine, for each of the three periods (i.e., the pre-peak, peak, and post-peak periods), the relationship between the size of a price increase in the peak rate period and the changes in the two distinct categories of household electricity consumption. For that reason, I quantitatively determine the relationship by utilizing the following econometric model:

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

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 those interaction terms 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}) presented in Table 5 are summarized graphically in Figure 8. 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 increased as the magnitude of a peak-hour price increase grew. 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. As well illustrated in the figure, 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. 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. 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. For the same reason as in the peak period, the aggregate treatment effects of the TOU tariffs described in the last row of Figure 8 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. 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. Altogether, as shown in the third column of the last row in Figure 8, 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.

3.3 Dynamics of Household Electricity Consumption under Time-Of-Use Electricity Pricing

The preceding results from my empirical analysis highlight that households were quite responsive to incremental changes in the peak-demand-hour price. As the peak-hour price increased compared to the flat rate, non-temperature-control-related electricity consumption continued to decline in the peak rate period. In contrast, as the peak-hour price increased, temperature-control-driven consumption did indeed fall, but these reductions in residential electricity consumption occurred outside of the peak rate period (i.e., in the pre- and post-peak periods). In this section, I will further examine what can drive these different patterns in the responses to TOU prices.

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 a peak TOU price by conserving their electricity consumption during peaks, 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 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 8, in the peak period, the reduction in non-temperature-control-related electricity consumption increased as the magnitude of a peak-rate-period price change under the TOU program grew. Non-temperature-control-driven electricity consumption for 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 a 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, the price increases in the peak rate period caused a spillover effect in those surrounding periods: a reduction in electricity consumption for non-temperature-control uses.

A remarkable point with respect to 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 reductions in not-for-heating electricity consumption in the surrounding periods declined as the magnitude of a peak-rate-period price change increased is well in line with load-shifting motivated by a monetary incentive coming from price differences. As shown in Figure 8, the relocation-associated behavioral change, in general, did not fully outweigh the conservation-relevant behavioral change in both periods.

In summary, with respect to non-temperature-control-driven electricity consumption, the households assigned to the treatment group responded to the TOU program, on the whole, via load-shedding as primary and load-shifting as secondary. 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 the figure, did not vary with the level of a peak-hour price increase.

With respect to temperature-control-related household electricity consumption, Figure 8 depicts that the treated households' primary response to the TOU program was also load-shedding. 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[29]—interestingly, and although statistically insignificant, the smaller the magnitude of a peak-demand-hour price increase, the larger the induced reduction in temperature-control-related consumption in the peak period. That is, the reduction violated 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 off-peak hours. 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 a price decrease or load-shifting. In other words, regarding temperature-control-driven household electricity consumption, in addition to the peak rate period, the price signals did not function well in the pre-peak period. In the post-peak period, although high daily HDDs incurred additional electricity consumption for heating after introducing TOU tariffs, which also cannot be justified by the price signals for the same reasons as in the pre-peak period, its amount was generally not large enough to fully offset, for given heating needs in a day, the reductions 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.

[29]See Figure 3.

Measuring the induced consumption reduction of households in Tariff Group D relative to Tariff Group A validates the load-shedding interpretation. Suppose that for treated residential consumers, load-shifting is a primary countermeasure against the TOU program. Then the residential consumers in Tariff Group D, compared to those in Tariff Group A, had more incentive to reallocate a portion of their peak-hour electricity consumption to off-peak hours because they faced a much larger price increase in the peak rate period as well as a much larger price decrease in the pre- and post-peak periods. So, compared to those in Tariff Group A, the households in Tariff Group D should consume more electricity in both periods surrounding the peak rate period, while their electricity consumption should be less in the peak rate period. However, Figure 9, which shows point estimates obtained by setting Tariff Groups A and D as the control and treatment groups, respectively, exhibits merely a slender hint of load-shifting only in the post-peak period. As illustrated in the figure, regarding non-temperature-control-driven household electricity consumption, there were apparent reductions in the peak rate period, while only a marginal increase in the post-peak period. Such patterns were also identified for temperature-control-related electricity consumption on cold days. Consequently, load-shifting played a minimal role in reshaping households' load profiles in and near the peak rate period.

3.3.2 Household Consumption Behavior in and near the Peak Rate Period

From Figure 8, 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 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.[30] 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

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

that use of electricity during the following period (i.e., during the peak rate period) in lieu of price signals. In Figure 8, 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.[31] 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.[32]

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 8, 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

[31] 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).

[32] 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/.

Real-Time Pricing (RTP), a more granular time-varying electricity tariff structure.[33] 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 4, 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 8, 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 TOU electricity pricing induces a larger reduction in household electricity consumption during peak hours as generation costs rise due to higher electricity demand, even though there were only within-day price variations under the price scheme. 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 Time-Of-Use 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.,

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

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). 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 10 depicts an alternative price scheme and additional gains from it. Under the price scheme proposed in 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. 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 a more significant reduction 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 is alleviated under the new 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.

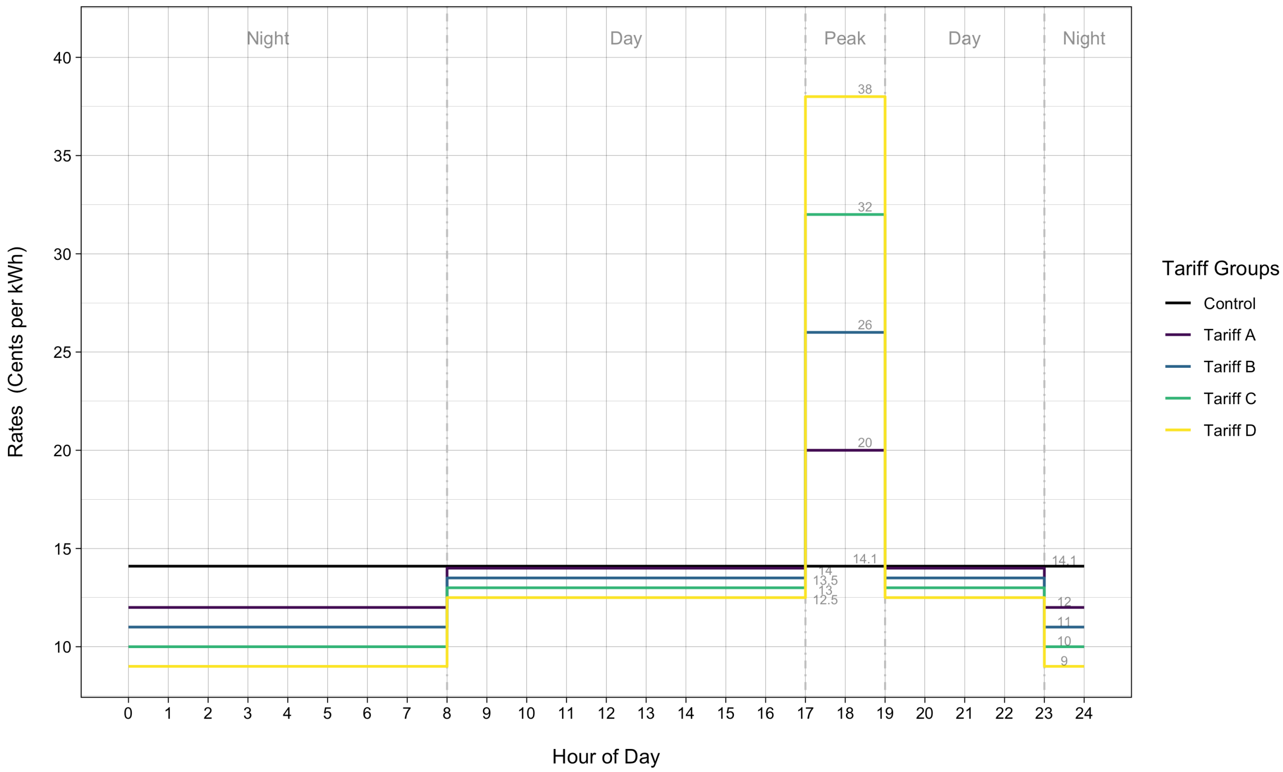

Figure 1: Time-Of-Use Pricing Structures

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.

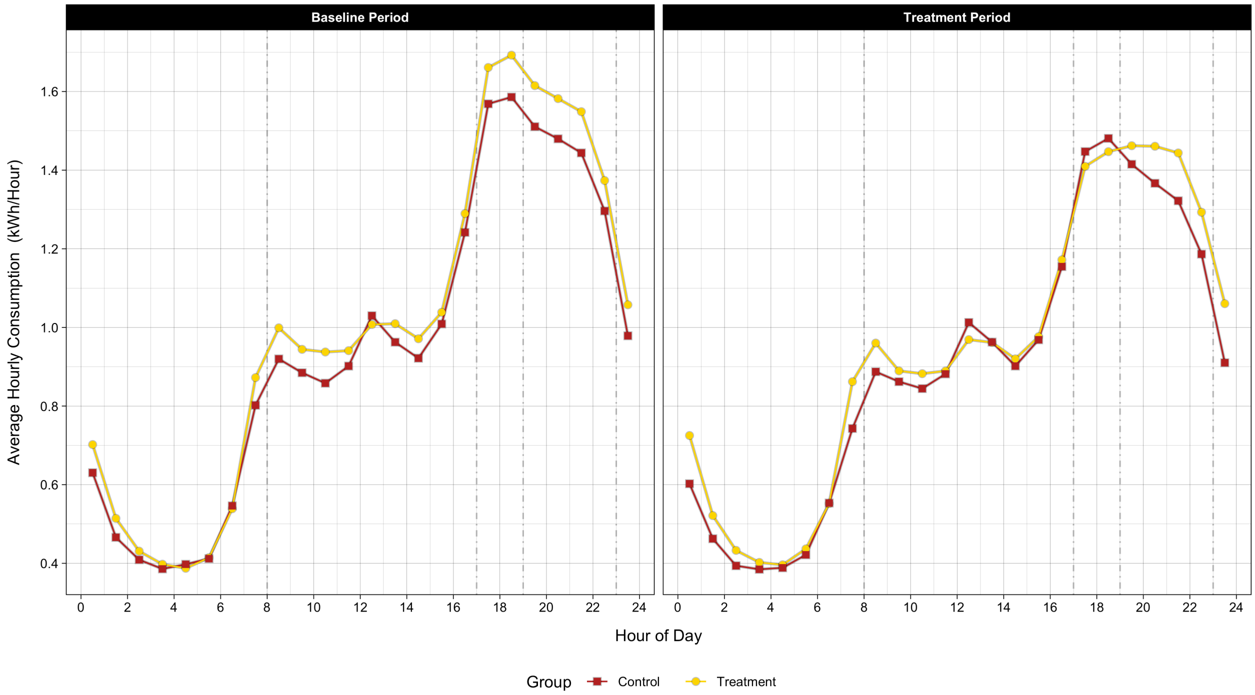

Figure 2: Average Hourly Electricity Consumption by Time of Day

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.

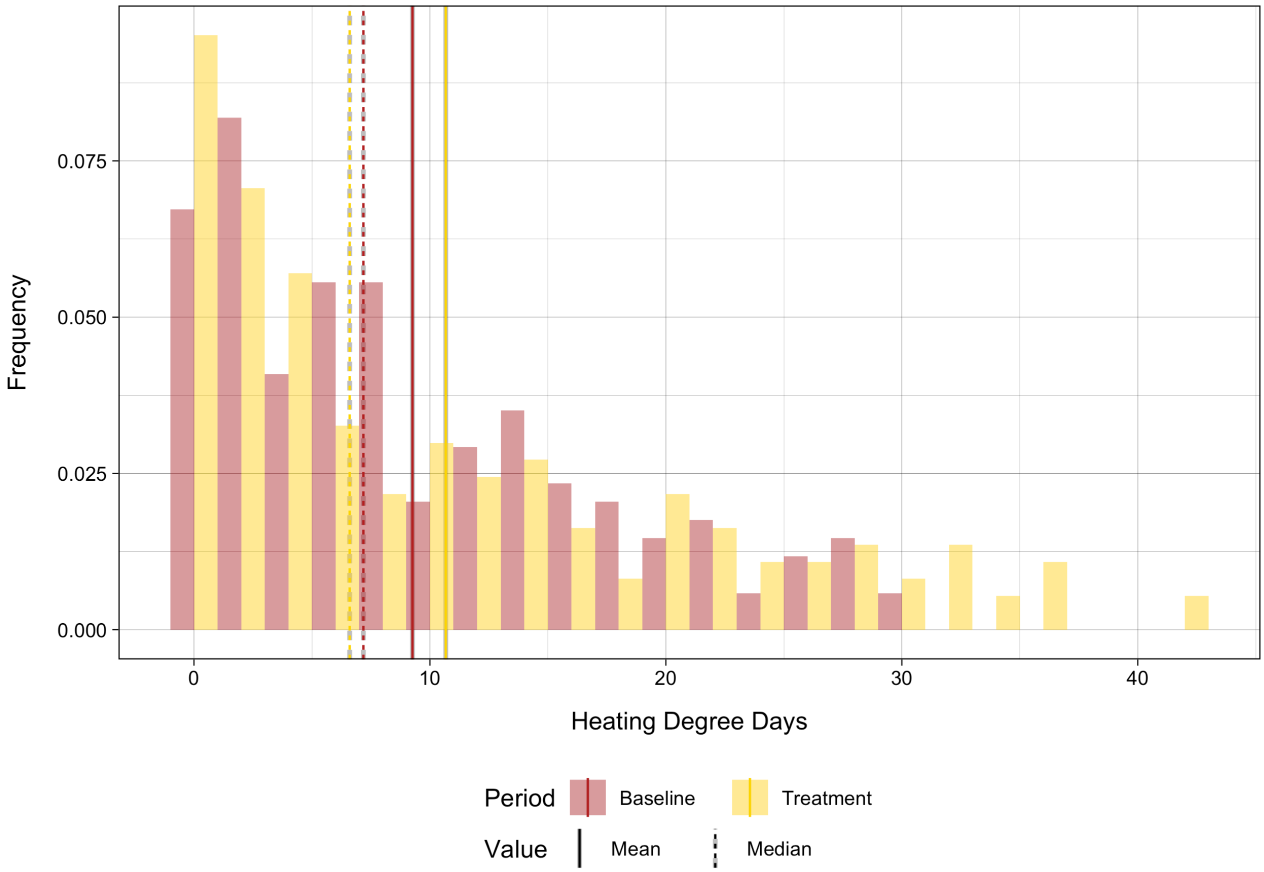

Figure 3: Distribution of Heating Degree Days during Experiment Periods

Note: This histogram shows the distribution of HDDs, with the mean and median values, in each experiment period. Only the second halves of 2009 and 2010 are utilized to generate the histogram.

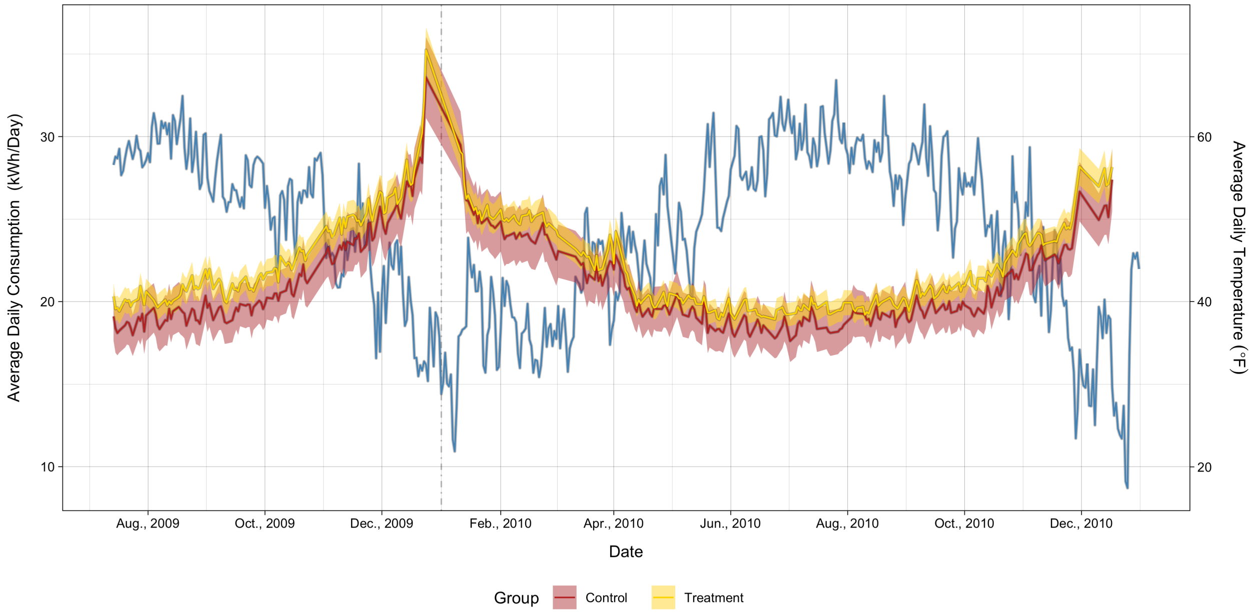

Figure 4: Average Daily Electricity Consumption

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.

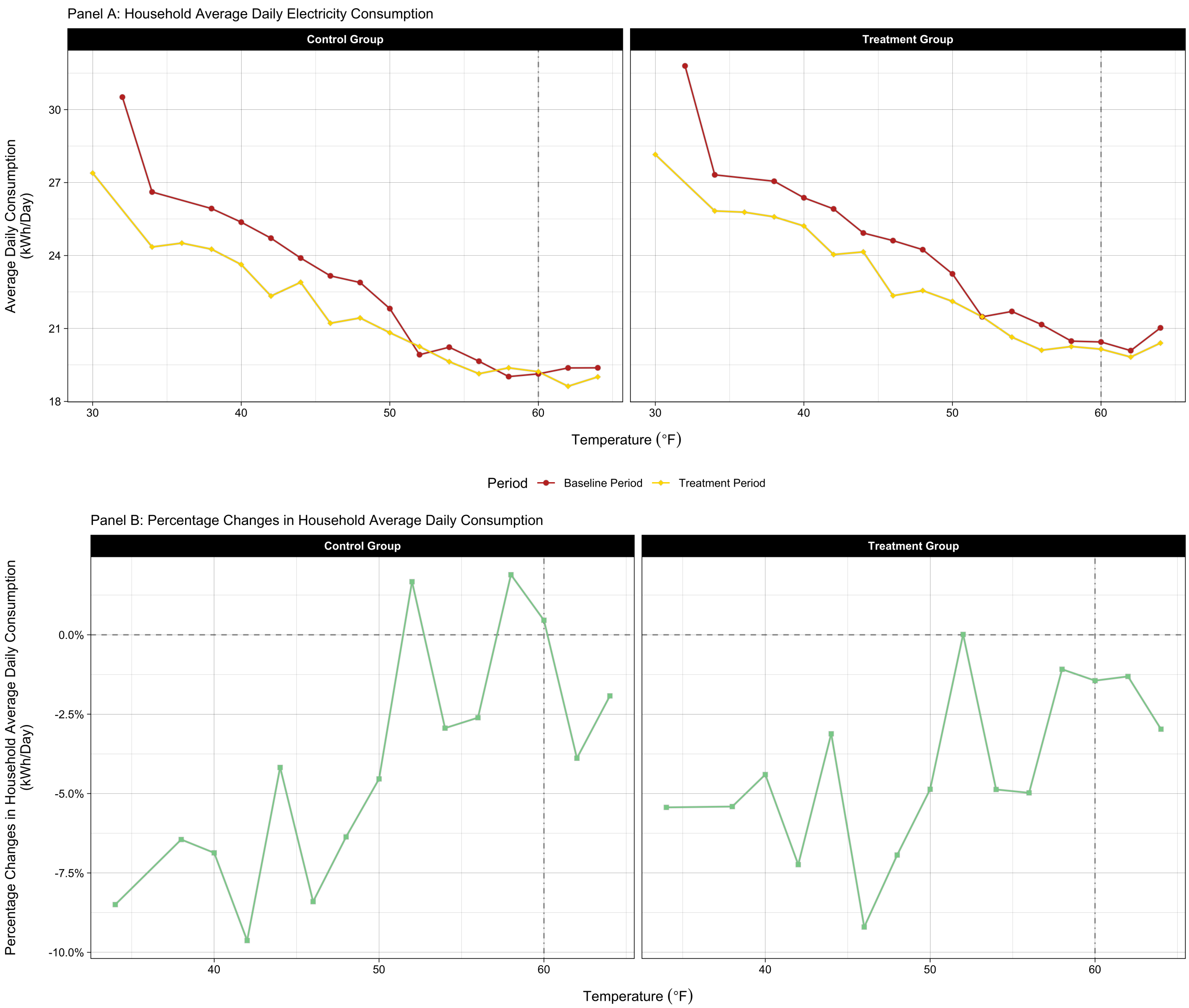

Figure 5: Pre- and Post-Treatment Household Average Daily Electricity Consumption

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.

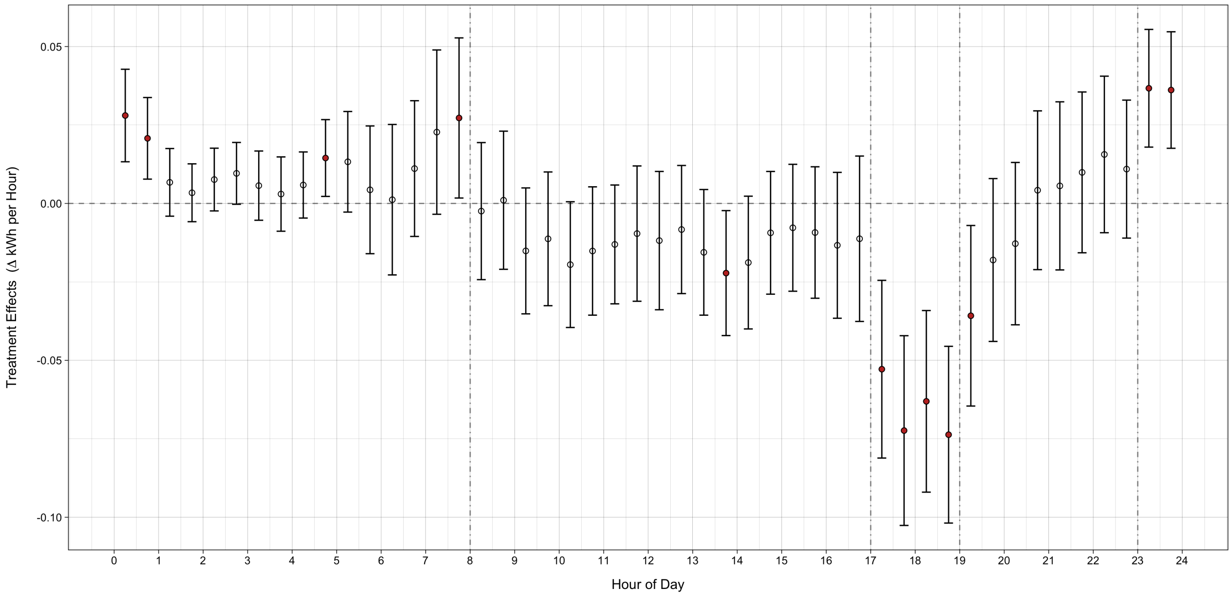

Figure 6: Half-hourly Average Treatment Effects

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.

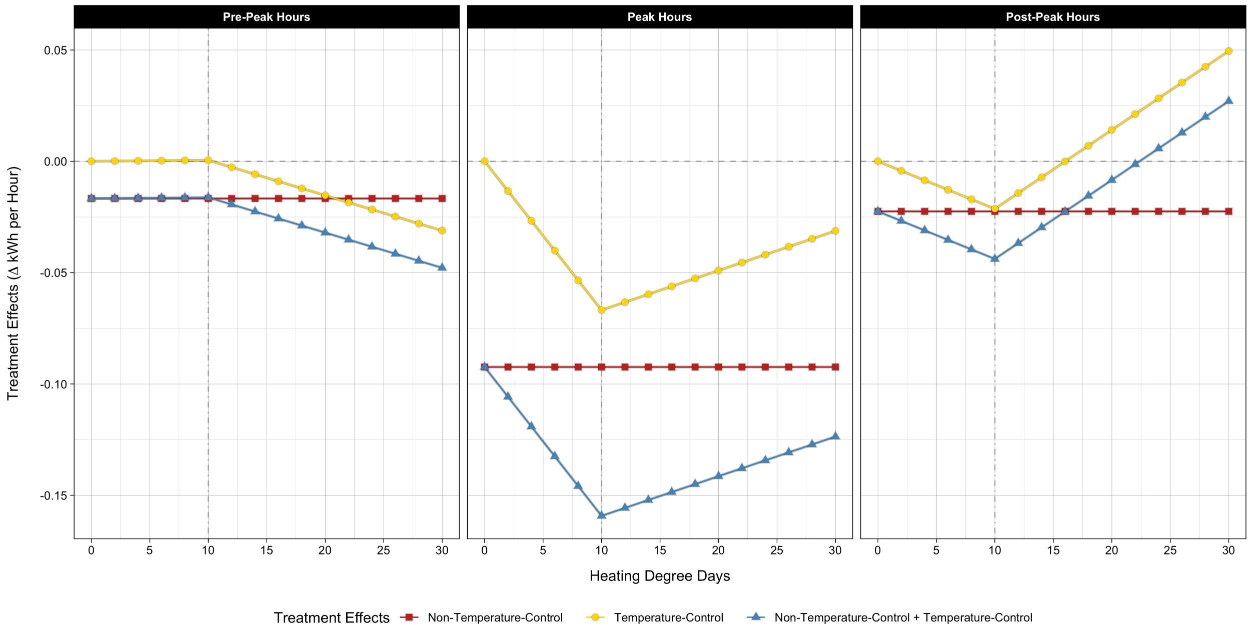

Figure 7: Breakdown of Hourly Average Treatment Effects

Note: This figure is a graphical summary of the regression results in the first three columns of Table 4. 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 variations. On the other hand, the changes in temperature-control-associated residential electricity consumption are a nonlinear function of daily HDDs.

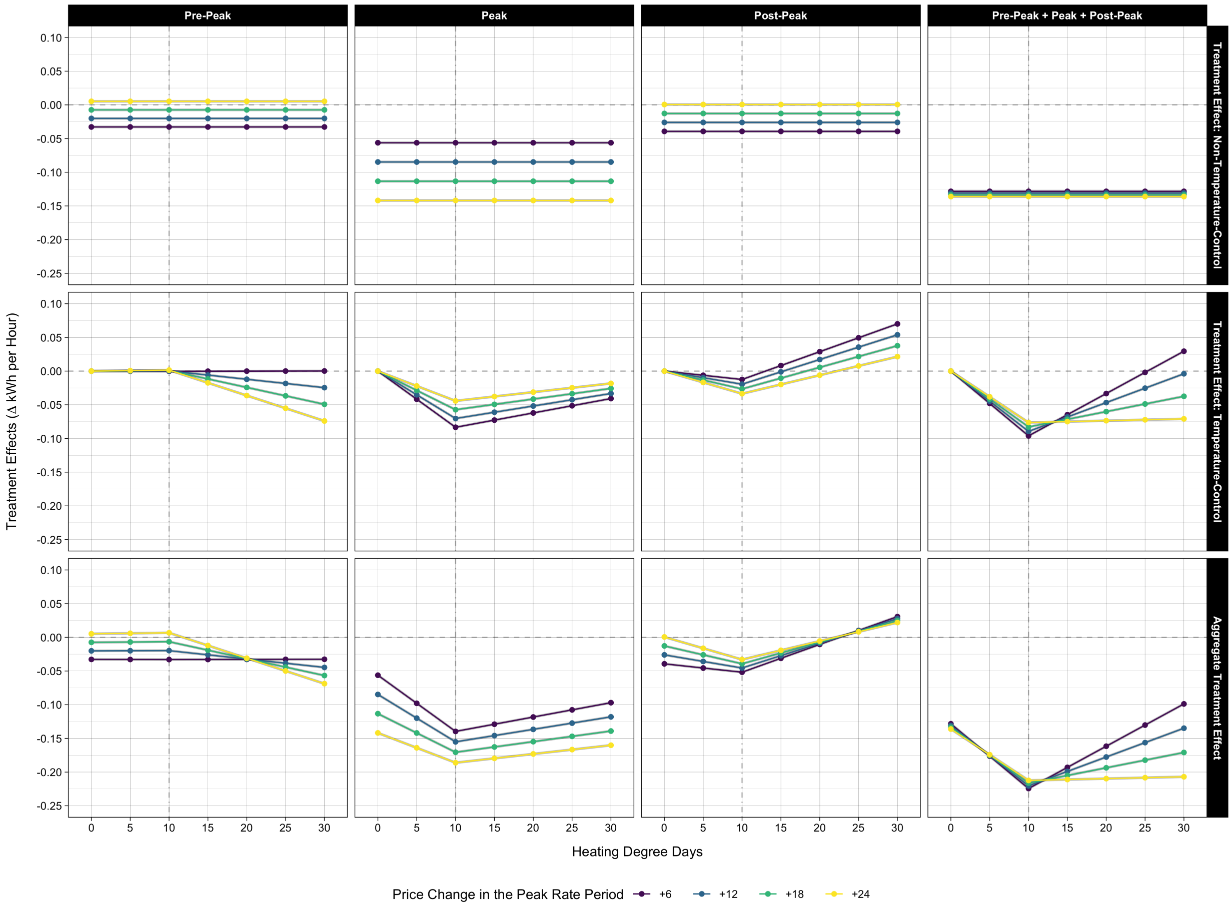

Figure 8: Treatment Effects as a Linear Function of Peak-hour Price Changes

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.

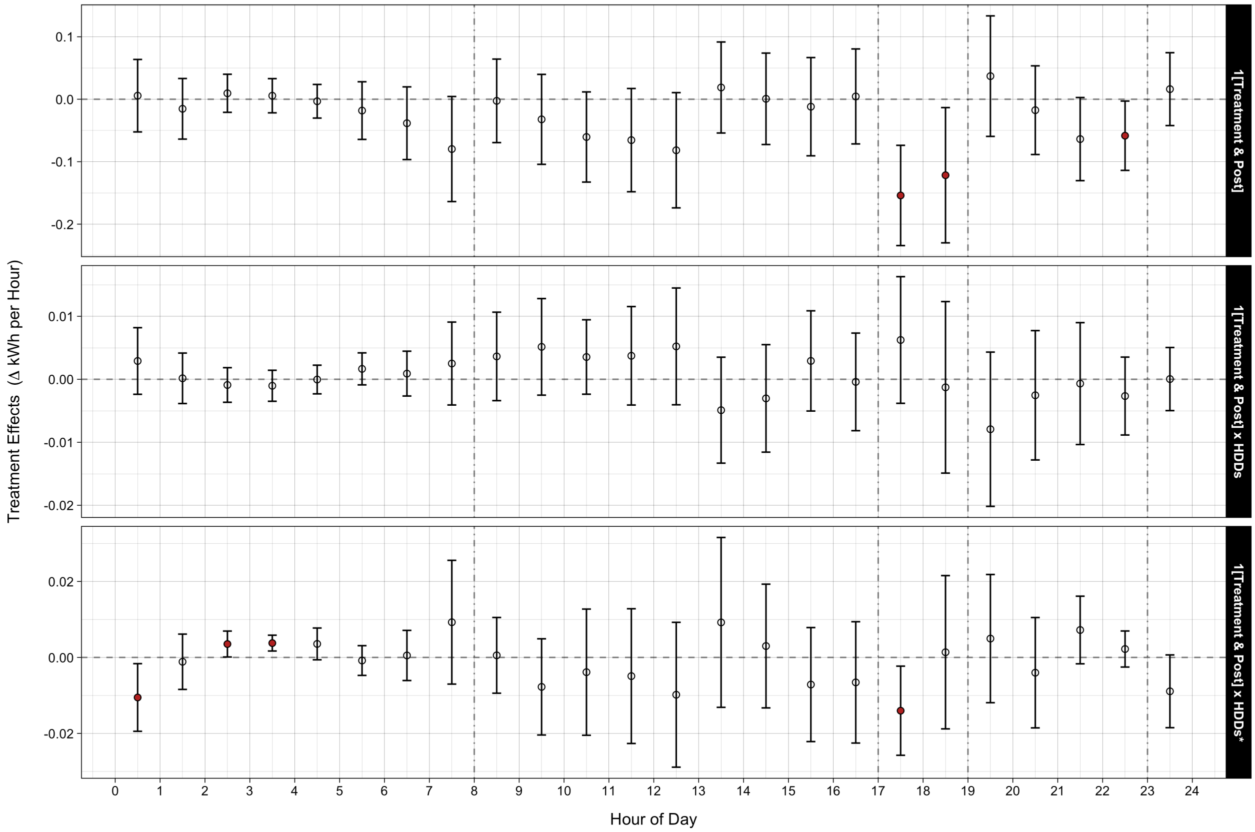

Figure 9: Relative Comparison of Tariff Group D to Tariff Group A

Note: This figure shows time profiles of hourly treatment effects measured by setting Tariff Groups A and D as the control and treatment groups. Each row in the figure corresponds to one of the three indicator variables of interest. The time profiles suggest only limited evidence of load-shifting.

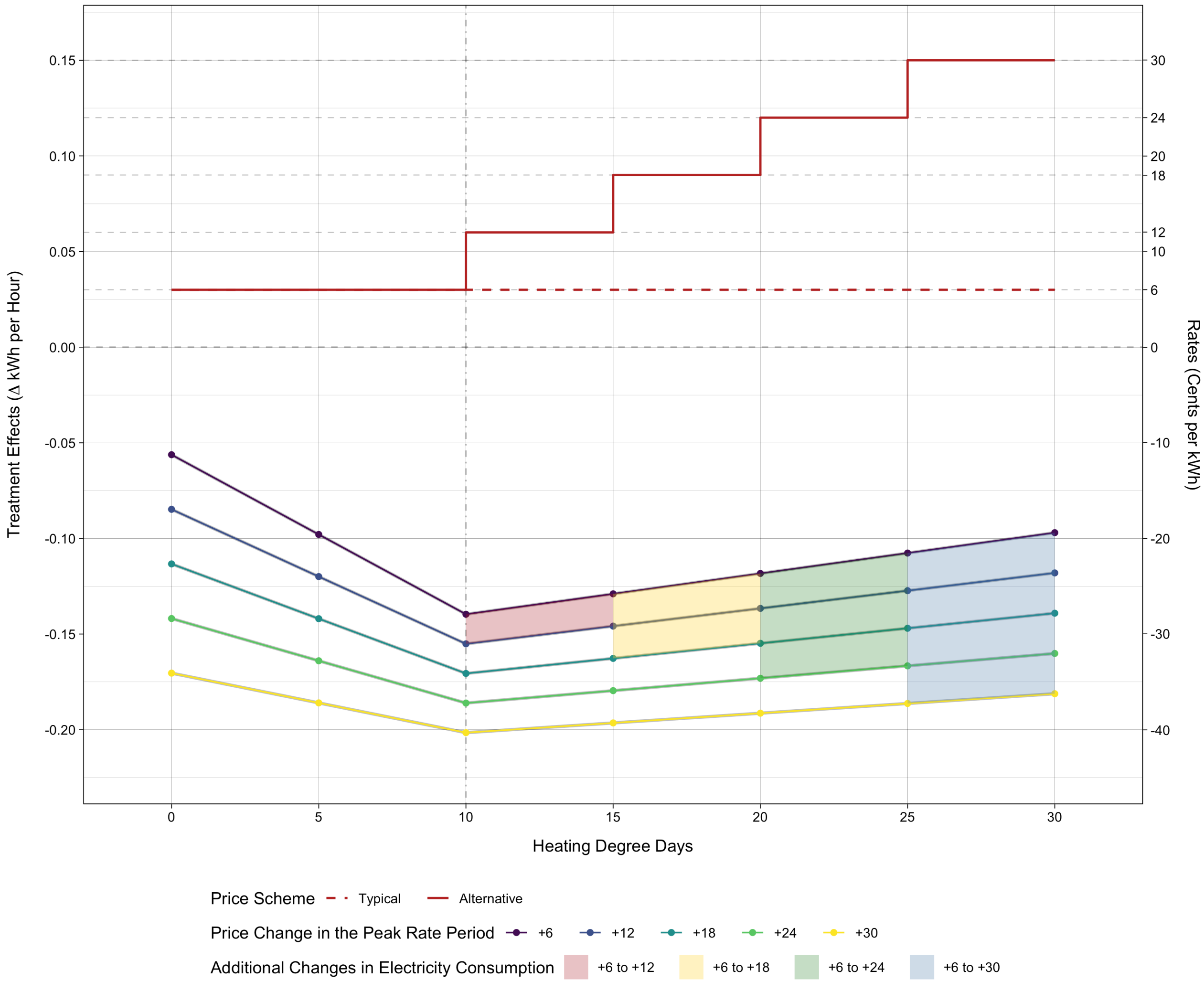

Figure 10: Additional Gains from an Alternative Electricity Pricing Scheme

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.

Table 0: 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

Table 1: 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: Third Level+?	0.265	(0.027)	0.344	(0.016)	0.078	(0.032)	0.014
Employed?	0.488	(0.031)	0.596	(0.016)	0.108	(0.035)	0.002
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: The variable descriptions with question mark suggest that these variables are binary.

Table 2: Correlations in Average Daily Temperatures between Weather Stations

Stations	Correlation Coefficients	
	For Sample Period	For Experiment Period
Ballyhaise	0.98291	0.98244
Belmullet	0.96089	0.96361
Cork Airport	0.97121	0.97130
Gurteen	0.98389	0.98307
Johnstown	0.98189	0.97958
Mace	0.95870	0.95921
Malin	0.95632	0.95705
Markree Castle	0.97194	0.97179
Moore Park	0.98057	0.97798
Mount Dillon	0.97945	0.97782
Mullingar	0.98876	0.98654
Newport Furnace	0.97015	0.97211
Oak Park	0.99074	0.98925
Shannon Airport	0.97696	0.97582
Sherkin Island	0.95342	0.95411

Note: For each weather station, historical weather data from the weather station at Dublin airport is utilized to compute the two correlation coefficients. The location of each weather station stated in the table is shown on a map in Figure 12. I do not provide the p-value of each correlation coefficient because it is arbitrarily small in magnitude. And the experiment period is the period between July 2009 to December 2010, while the sample period is the second half of 2009 and 2010.

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)
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: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 4: Breakdown of Hourly Average Treatment Effects

	Hourly Electricity Consumption (kWh/Hour)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbb{1}$[Treatment & Post]	-0.017	-0.092^{***}	-0.022	-0.057^{*}	-0.127^{***}	-0.078^{**}	-0.189^{***}
	(0.020)	(0.025)	(0.024)	(0.030)	(0.039)	(0.031)	(0.041)
$\mathbb{1}$[Treatment & Post] $\times$ HDDs	0.00005	-0.007^{**}	-0.002	-0.010^{***}	-0.002	-0.004	-0.009
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)	(0.006)
$\mathbb{1}$[Treatment & Post] $\times$ HDDs*	-0.002	0.008^{***}	0.006^{*}	0.013^{***}	0.003	0.005	0.011^{*}
	(0.003)	(0.003)	(0.003)	(0.005)	(0.006)	(0.003)	(0.006)
Description of Period	Pre-Peak	Peak	Post-Peak	Peak	Peak	Peak	Peak
Period of Hours	15 to 16	17 to 18	19 to 20	17 to 18	17 to 18	17 to 18	17 to 18
Tariff Group	All	All	All	A	B	C	D
Price Change in the Peak Rate Period	[-]	[-]	[-]	+6	+12	+18	+24
Knot	10	10	10	10	10	10	10
FEs: Day of Week by Half-Hourly Time Window	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,006,200	1,006,200	1,006,200	506,540	326,800	511,700	331,960
Adjusted R^2	0.024	0.047	0.040	0.046	0.044	0.044	0.045

Note: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 5: Hourly Treatment Effects as a Linear Function of Peak-rate-period Price Changes

	Hourly Electricity Consumption (kWh/Hour)		
	(1)	(2)	(3)
$\mathbb{1}$[Treatment & Post]	-0.045	-0.028	-0.053
	(0.029)	(0.035)	(0.035)
$\mathbb{1}$[Treatment & Post] $\times$ ΔPC	0.002	-0.005^{**}	0.002
	(0.002)	(0.002)	(0.002)
$\mathbb{1}$[Treatment & Post] $\times$ HDDs	-0.0001	-0.010^{**}	-0.001
	(0.004)	(0.004)	(0.004)
$\mathbb{1}$[Treatment & Post] $\times$ HDDs*	0.001	0.012^{**}	0.005
	(0.005)	(0.006)	(0.005)
$\mathbb{1}$[Treatment & Post] $\times$ HDDs $\times$ ΔPC	0.00001	0.0002	-0.0001
	(0.0002)	(0.0002)	(0.0003)
$\mathbb{1}$[Treatment & Post] $\times$ HDDs* $\times$ ΔPC	-0.0002	-0.0003	0.00004
	(0.0003)	(0.0003)	(0.0003)
Description of Period	Pre-Peak	Peak	Post-Peak
Period of Hours	15 to 16	17 to 18	19 to 20
Knot	10	10	10
FEs: Day of Week by Half-Hourly Time Window	Yes	Yes	Yes
Observations	1,006,200	1,006,200	1,006,200
Adjusted R^2	0.024	0.047	0.040

Note: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

A Appendixes

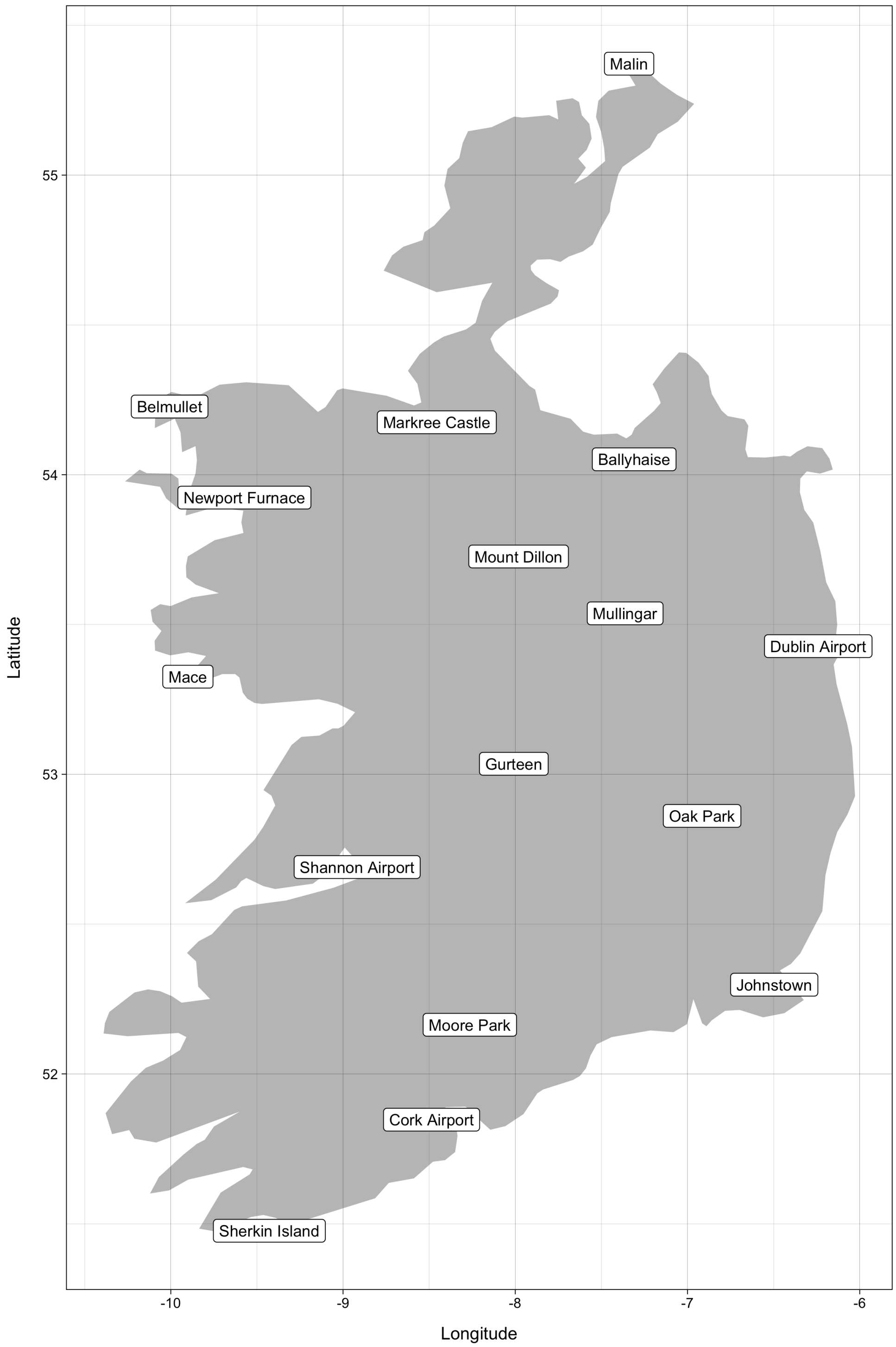

Figure 12: Weather Stations from which Historical Weather Data have been collected

Note: This figure demonstrates the location of each weather station listed in Table 2. As is evident from the map, the weather stations are distributed throughout Ireland.

Table 5: Hourly Average Treatment Effects in and near the Peak Rate Period

	Hourly Electricity Consumption (kWh/Hour)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\mathbb{1}$[Treatment & Post]	-0.048^{***}	-0.053^{*}	-0.002	-0.049	-0.125^{***}	-0.161^{***}	-0.119^{***}	-0.249^{***}	-0.082^{***}	-0.055^{*}	-0.015	-0.113^{**}
	(0.016)	(0.027)	(0.017)	(0.031)	(0.020)	(0.036)	(0.022)	(0.044)	(0.020)	(0.030)	(0.021)	(0.048)
Description of Period	Pre-Peak	Pre-Peak	Pre-Peak	Pre-Peak	Peak	Peak	Peak	Peak	Post-Peak	Post-Peak	Post-Peak	Post-Peak
Period of Hours	15 to 16	15 to 16	15 to 16	15 to 16	17 to 18	17 to 18	17 to 18	17 to 18	19 to 20	19 to 20	19 to 20	19 to 20
Tariff Group	A	B	C	D	A	B	C	D	A	B	C	D
Price Change in the Peak Rate Period	+6	+12	+18	+24	+6	+12	+18	+24	+6	+12	+18	+24
FEs: Household by Half-Hourly Time Window	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs: Day of Week by Half-Hourly Time Window	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs: Month of Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	506,540	326,800	511,700	331,960	506,540	326,800	511,700	331,960	506,540	326,800	511,700	331,960
Adjusted R^2	0.312	0.330	0.320	0.327	0.384	0.397	0.383	0.367	0.371	0.389	0.376	0.361

Note: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 6: Breakdown of Hourly Average Treatment Effects

	Hourly Electricity Consumption (kWh/Hour)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HDDs	0.016***	0.016***	0.016***	0.015***	0.047***	0.047***	0.047***	0.047***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
HDDs*	0.010	0.009	0.009	0.010	−0.018***	−0.018***	−0.018***	−0.018***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
𝟙[Treatment]	0.009	0.106	−0.014	0.174**	0.057	0.189**	−0.017	0.150**
	(0.050)	(0.071)	(0.049)	(0.072)	(0.055)	(0.083)	(0.052)	(0.072)
𝟙[Treatment] × HDDs	0.001	0.004	0.001	0.0003	0.009**	0.008	0.008**	0.011
	(0.003)	(0.005)	(0.003)	(0.004)	(0.004)	(0.007)	(0.004)	(0.007)
𝟙[Treatment] × HDDs*	−0.0001	−0.012*	0.0004	0.002	−0.012***	−0.016**	−0.013***	−0.008
	(0.004)	(0.006)	(0.003)	(0.005)	(0.004)	(0.008)	(0.004)	(0.007)
𝟙[Post]	0.014	0.015	0.014	0.011	0.048	0.049	0.047	0.047
	(0.022)	(0.022)	(0.022)	(0.023)	(0.040)	(0.040)	(0.040)	(0.040)
𝟙[Post] × HDDs	−0.007	−0.007	−0.007	−0.006	−0.015**	−0.015**	−0.015**	−0.015**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
𝟙[Post] × HDDs*	0.002	0.002	0.002	0.001	0.006	0.007	0.006	0.006
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
𝟙[Treatment & Post]	−0.038	−0.039	0.020	−0.039	−0.040	−0.050	0.006	−0.025
	(0.023)	(0.030)	(0.026)	(0.038)	(0.029)	(0.037)	(0.027)	(0.040)

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Table 6 – continued from previous page

	Hourly Electricity Consumption (kWh/Hour)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$[Treatment & Post] × HDDs	0.001	−0.003	−0.0002	0.001	−0.003	0.0005	0.0003	−0.009
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.005)	(0.003)	(0.006)
$\mathbb{1}$[Treatment & Post] × HDDs*	−0.002	0.008	−0.004	−0.005	0.005	0.010	0.004	0.008
	(0.004)	(0.006)	(0.004)	(0.006)	(0.004)	(0.007)	(0.003)	(0.006)
Description of Period	Pre-Peak	Pre-Peak	Pre-Peak	Pre-Peak	Post-Peak	Post-Peak	Post-Peak	Post-Peak
Period of Hours	15 to 16	15 to 16	15 to 16	15 to 16	19 to 20	19 to 20	19 to 20	19 to 20
Tariff Group	A	B	C	D	A	B	C	D
Price Change in the Peak Rate Period	+6	+12	+18	+24	+6	+12	+18	+24
Knot	10	10	10	10	10	10	10	10
FEs: Day of Week by Half-Hourly Time Window	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	506,540	326,800	511,700	331,960	506,540	326,800	511,700	331,960
Adjusted R^2	0.024	0.024	0.023	0.025	0.041	0.040	0.039	0.043

Note: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 7: Hourly Treatment Effects as a Linear Function of Peak-Rate-Period Price Changes

	Hourly Electricity Consumption (kWh/Hour)		
	(1)	(2)	(3)
HDDs	0.016^{***}	0.042^{***}	0.047^{***}
	(0.004)	(0.006)	(0.004)
HDDs*	0.010	0.001	-0.018^{***}
	(0.007)	(0.010)	(0.007)
$\mathbb{1}$[Treatment]	-0.020	-0.018	0.064
	(0.059)	(0.073)	(0.065)
$\mathbb{1}$[Treatment] $\times$ ΔPC	0.004	0.005	-0.0003
	(0.003)	(0.004)	(0.003)
$\mathbb{1}$[Treatment] $\times$ HDDs	0.001	0.013^{**}	0.009
	(0.004)	(0.005)	(0.005)
$\mathbb{1}$[Treatment] $\times$ HDDs*	-0.003	-0.011^{*}	-0.014^{***}
	(0.005)	(0.006)	(0.005)
$\mathbb{1}$[Treatment] $\times$ HDDs $\times$ ΔPC	-0.00001	-0.0004	0.00003
	(0.0002)	(0.0003)	(0.0003)
$\mathbb{1}$[Treatment] $\times$ HDDs* $\times$ ΔPC	0.0001	0.0003	0.0001
	(0.0003)	(0.0003)	(0.0003)
$\mathbb{1}$[Post]	0.013	0.045	0.047
	(0.022)	(0.036)	(0.040)
$\mathbb{1}$[Post] $\times$ HDDs	-0.007	-0.015^{*}	-0.015^{**}
	(0.005)	(0.008)	(0.006)

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Table 7 – continued from previous page

	Hourly Electricity Consumption (kWh/Hour)		
	(1)	(2)	(3)
$\mathbb{1}$[Post] $\times$ HDDs*	0.002	0.007	0.006
	(0.008)	(0.013)	(0.009)
$\mathbb{1}$[Treatment & Post]	-0.045	-0.028	-0.053
	(0.029)	(0.035)	(0.035)
$\mathbb{1}$[Treatment & Post] $\times$ ΔPC	0.002	-0.005^{**}	0.002
	(0.002)	(0.002)	(0.002)
$\mathbb{1}$[Treatment & Post] $\times$ HDDs	-0.0001	-0.010^{**}	-0.001
	(0.004)	(0.004)	(0.004)
$\mathbb{1}$[Treatment & Post] $\times$ HDDs*	0.001	0.012^{**}	0.005
	(0.005)	(0.006)	(0.005)
$\mathbb{1}$[Treatment & Post] $\times$ HDDs $\times$ ΔPC	0.00001	0.0002	-0.0001
	(0.0002)	(0.0002)	(0.0003)
$\mathbb{1}$[Treatment & Post] $\times$ HDDs* $\times$ ΔPC	-0.0002	-0.0003	0.00004
	(0.0003)	(0.0003)	(0.0003)
Description of Period	Pre-Peak	Peak	Post-Peak
Period of Hours	15 to 16	17 to 18	19 to 20
Knot	10	10	10
FEs: Day of Week by Half-Hourly Time Window	Yes	Yes	Yes
Observations	1,006,200	1,006,200	1,006,200
Adjusted R^2	0.024	0.047	0.040

Note: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

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