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1 Introduction

These days many utilities are moving towards Time-of-Use (TOU) electricity tariff structures that raise the rate for peak-demand hours to the predetermined level, which does not vary across days. Many evaluations of experiments that assessed how residential consumers respond to TOU rates consistently document reductions in electricity consumption during peak hours. Those studies, however, do not examine how such reductions in household electricity consumption are achieved. In this research, to understand the mechanism of the demand reductions in detail, I decompose the decline in residential electricity consumption into two different sources of electricity savings: 1) electricity savings derived from the reduction in electricity consumption for temperature-control uses (e.g., cooling and heating), and 2) electricity savings from non-temperature-control uses (e.g., lighting, operating appliances, and cooking). Furthermore, instead of focusing only on the peak hours, my empirical analysis also covers intervals near the peak rate period around peak hours (i.e., 2-hour-length pre- and post-peak intervals), in which the level of household electricity consumption changed a lot.

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. Due to Irish households' widespread use of non-electric fuels for space and water heating, the sample utilized in the empirical analysis only includes meter readings from non-electric heating households. Using Difference-in-Differences (DID) strategy, I estimate the Average Treatment Effects (ATEs) of the TOU prices on household electricity consumption. To be specific, I measure how electricity savings from the TOU program vary with average daily temperatures. In addition, I also estimate how the savings alter with the magnitude of price changes during peak hours. By doing so, I find that around peak hours, the electricity savings stemming from the two distinct drivers of household electricity consumption (i.e., temperature-control and non-temperature-control uses) evolve differently depending on the point in time where the electricity is consumed, daily Heating Degree Days (HDDs), and the size of peak-hour price spikes.

The empirical analysis reveals that the TOU-price-causing variations in residential electricity demand are not restricted to the peak rate period. In addition to the consumption reductions during the peak rate period, my results show that participating households tend to cut their electricity consumption down before directly experiencing a price jump to the predetermined level. Moreover, such pre-adjustments are observed both from non-for- and for-heating electricity uses.

From the detailed analysis, I also find that temperature-control-use-associated electricity savings are a non-linear function of daily HDDs around peak hours. In other words, for a given peak-hour price jump, the impact of the TOU electricity tariffs on residential demand at an instant of time varies with daily HDDs. Specifically, the changes in household electricity consumption for heating show a U-shape profile over daily HDDs in the peak rate period, while those in the pre- and post-peak intervals do not emerge until daily HDDs are sufficiently sizable.

The most absorbing finding from the empirical analysis is that households are highly responsive to the level of price changes in peak-demand hours. In the two-hour-length interval just before the peak-demand hours, the HDD-varying treatment effect on household electricity consumption for temperature-control uses is proportional to the size of the peak-demand-hours rate changes. On the other hand, the treatment effect on non-temperature-control-use-related electricity demand is inversely proportional to it. Interestingly, those relationships are flipped for the peak-rate-period electricity consumption. To be specific, the savings related to the for-heating use of electricity decrease as the price jumps in the peak-demand interval become more prominent, while the savings stemming from the electricity consumption for non-for-heating purposes is proportional to the jumps. Due to the opposite order of the magnitude of the demand reductions, the high sensitivity of household electricity consumption to the TOU tariffs around peak hours is masked. Indeed, this is precisely the result discussed in Prest (2020), which also utilizes the CER experiment datasets.[1]

How households adapted their consumption behavior to the TOU tariff structures newly introduced can be deduced from those empirical findings above. Regarding the electricity consumption for non-temperature-control uses, the households assigned to the treatment group in the experiment simply reduced their demand around the peak rate period in lieu of reallocating it to off-peak hours. In other words, participating households reacted to the price jumps in peak demand hours, not through load-shifting but load-shedding. On the other hand, for-heating-associated electricity savings accompanied more complicated behavioral changes. Households adjusted their electricity consumption during the pre- and post-peak hours only when HDDs were large enough. And the reductions obtained from the pre-adjustment seem to lead to fewer savings in the following period (i.e., the peak rate period), especially on freezing days.

Those findings disclose a veiled advantage of TOU electricity pricing: day-varying effects on residential electricity savings. Let us suppose that the electricity savings obtained by adopting the TOU prices stem entirely from the reductions in non-temperature-control uses. In that case, intuitively, the magnitude of the savings does not vary across days. In other words, the amount of the savings does not depend on across-day temperature variations when residential demand for electricity peaks. However, my empirical results illustrate that on days with moderate heating needs, a sizable share of the electricity savings does stem from reductions in the use of electricity for temperature-control uses. Consequently, even though the TOU rates do not change across days, the tariff structures already induce substantial reductions in electricity consumption on typical winter days, in terms of daily HDDs, in Ireland.

The empirical results also provide new insights into the potential benefits of adopting even more dynamic price structures, e.g., Real-Time Pricing (RTP).[2] As discussed earlier, the U-shaped evolving pattern of the temperature-control-use-associated electricity savings over daily HDDs in the peak rate period implies that

[1] Prest (2020) expresses the result as follows: "Most of the overall response comes at the smallest price increase, with higher prices yielding strongly diminishing returns."

[2] Under RTP, retail prices vary across not only hours of days but days according to contemporaneous generating costs.

TOU electricity pricing becomes less effective on days with extreme outside temperatures. So on those days that the grid is most burdened, in turn, the most significant electricity savings are required, the additional gains from switching from TOU prices to RTPs might be smaller than many economists have thought. Nevertheless, considering that a high price change in the peak-demand hours prevents the temperature-control-use-driven electricity savings from disappearing, allowing the peak-hour prices to rise by synchronizing it with daily HDDs would induce moderately more savings on high-demand days.

In addition, the identified gap, in terms of the most attainable for-heating-use-related electricity savings, between the lowest and the highest rate changes in the peak rate period suggests the potential gains from adopting automation technologies. As already discussed, the gap is likely a side effect of households' behavior change during the pre-peak interval. Hence, if it is possible to impede such changes in temperature-control-related electricity consumption from pre-peak to peak hours by exploiting an automation instrument, like an automated thermostat, more electricity savings can be achieved under TOU electricity pricing.

To sum, the results from my empirical analysis extend the previous work by decoupling temperature-control-use-related electricity savings from the entire TOU-pricing-causing demand reductions. My results demonstrate that around peak hours, the savings from the two different sources sensitively vary according to the magnitude of the price changes in the peak rate period. That is, prices still matter under TOU tariff structures. Moreover, the day-varying electricity savings under TOU prices suggest a vital policy implication: shifting from TOU towards RTP-like pricing can improve residential electricity savings on extremely cold days. In addition, examining the electricity savings from two distinct sources, not in the peak rate period but around the peak rate 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[3]

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 kWh). Also, they received a thank-you payment of 25 cents after pre- and post-trial surveys. All credits were

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

distributed outside the treatment period to avoid unintended effects on participants' electricity consumption.[4]

The households who voluntarily opt-in to the experiment were randomly assigned to control and treatment groups.[5] 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.[6] 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.[7]

Figure 1: Time-Of-Use Pricing Structures

[4]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.

[5]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.

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

[7]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.

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 non-holiday weekdays in the published electricity consumption data because the TOU rates were active 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.[8] Moreover, among the non-electric-heating households, those with unreliable meter reads are excluded from the sample.[9] This process results in 4,096 households.

The control and treatment groups in the sample are largely balanced, as shown in Table 2. Such indifferences between the two groups over many observables are consistent with previous studies examining the CER

[8]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 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. Second, as Figure 4 demonstrates, even non-electric-heating households consumed more electricity as temperatures decreased. In other words, even non-electric-heating households consumed more electricity as temperatures decreased. In other words, electricity is essential for non-electric-heating households to warm their space or water.

[9]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.

experiment dataset.[10]

Table 1: Treatment and Control Group Assignments

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

Figure 2: Average Consumption by Hour of Day

2.3 Description of Weather Data

In this research, 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. 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, the primary objective of this paper is to decompose the TOU-price-inducing demand reductions into two parts–reductions in temperature-control and non-temperature-control uses. Since the electricity consumption for temperature-control uses is driven by weather, especially temperatures, it is necessary to link the 30-minute interval consumption data and reliable weather data with an appropriate level of resolution.

The electricity savings associated with for-heating electricity consumption are disaggregated using average daily temperatures from the total savings resulting from the introduction of TOU prices. More granular temperatures, like hourly temperatures, are not a dominant determinant of electricity demand for temperature-control uses 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. Furthermore, as shown in Figure 2, their electricity demand is the lowest in the early morning, the coldest time of the day. Considering those two points, I measure the TOU-tariff-inducing reductions in electricity consumption conditional on the average heating need in a given day.

I exploit hourly temperature data for the Dublin airport weather station, provided by Met Éireann, Ireland's National Meteorological Service, to compute average daily temperatures. There is no available location infor-

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

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).

mation 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 3, the temperature correlations between the Dublin station and stations near densely populated cities are evident. Because of the positive 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). The upper part of Figure 7 shows that many days in the treatment period had lower average daily temperatures than the lowest one during the baseline period. The evolving pattern of heating-purpose demand for electricity on days with extreme temperatures could be significantly different under distinct rate structures–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.

Table 3: Correlations in Temperature for Major Cities in Ireland

Figure 3: Average Daily Temperature by Date

2.4 Empirical Strategy

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

Figure 4, 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.[11] 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 occur, on average, in response to the deployment

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

of the TOU tariffs but also how their impact varies 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 are smaller than those of the treated households.[12] 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.[13] 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 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.[14] That is, I estimate the ATEs of the dynamic prices

[12] 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.

[13] 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.

[14] 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 XYZ-1, 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 XYZ-2, 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

on household electricity demand by exploiting the within-household electricity consumption changes across not only rate periods but temperatures.[15]

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

3 Empirical Analysis and Results

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

3.1.1 Half-hourly Average Treatment Effects

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

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

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

Figure 6: Half-Hourly Average Treatment Effects

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 XYZ-2 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.

[15]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.

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.), during which the inefficiency of fixed flat rate tariff is greatly intensified, show dominant electricity savings. Although household electricity consumption altered considerably in two-hour-length intervals just before and after the peak rate period (i.e., from 3:00 p.m. to 5:00 p.m. and from 7:00 p.m. to 9:00 p.m., respectively), the TOU prices are unlikely to provoke significant changes in households' consumption behavior, except the immediate meter-reading period, in the intervals. But it is difficult to believe that the participating households managed their electricity consumption precisely along with the price variations during the peak rate period. It is rather likely that they adjusted their consumption behavior in and near peak hours. For this reason, in the following empirical analysis, I continually focus on household electricity demand responses to the time-varying prices in the three intervals of two hours.

3.1.2 Hourly Average Treatment Effects around the Peak Rate Period

Estimating by-tariff-group ATEs around the peak rate period allows us to justify whether or not the law of demand is satisfied between the responsiveness of Irish households and the magnitudes of price changes in TOU electricity pricing.[16] 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, as the response variable, kWh_{ith} that 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 two-hour-length intervals included in rate period p. Table **??** summarizes the regression results.

The measured peak-rate-period ATEs re-confirm the finding suggested in Prest (2020): a critical determinant of the effectiveness of TOU electricity pricing in the peak rate period is nothing more than its existence. As demonstrated in Table **??**, the estimated ATEs for the peak-demand hours generally follow the law of demand. In other words, the reductions in household demand for electricity in the peak rate period grow with the degree of price changes in that period. But the marginal gain of the time-varying price structure is diminishing.

Interestingly, the law of demand does not hold in both the pre- and post-peak intervals. In spite of the price drops in those intervals, compared to the flat rate of 14.1 cents per kWh, the treated households reduced their electricity consumption. Although the mechanism that caused the changes in residential electricity consumption is not explicit, such changes evidently suggest that the households assigned to the treatment group adjusted their electricity consumption not only prior to but also following the price spikes in the peak rate period. That is, the TOU tariffs have some spillover effects on household demand for electricity in the off-peak intervals.

[16] 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.

The results discussed above collectively imply that in and near peak-demand hours, at least one of the two distinct sources of electricity savings from TOU pricing, temperature-control- and non-temperature-control-related electricity consumption, is driven by the magnitude of tariff changes in the peak rate period. Motivated by this implication, the relative responsiveness of the two drivers of electricity savings to the TOU tariff structures is quantified in the following section.

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

3.2.1 Breakdown of Household Responses around the Peak Rate Period

I decompose TOU-tariff-causing reductions in household electricity consumption around the peak rate period into two parts to determine the share of electricity savings stemming from two distinct sources: savings from non-temperature-control and temperature-control electricity uses. Here, the non-temperature-control-related electricity savings mean the reductions in electricity demand that are stably achievable regardless of each day's weather conditions, especially temperatures. That is, the savings associated with non-temperature-control electricity uses do not vary across days. On the contrary, the latter savings strictly depend on daily HDDs, which fluctuate daily. Specifically, the temperature-control-associated electricity savings are additional savings that appear only on days with non-zero daily HDDs due to for-heating electricity consumption in households. Isolating the impact of the TOU prices on household electricity demand for temperature-control uses from the total reductions in electricity demand enables us to know how differently the TOU tariff structures function from day to day, whose implications will be discussed later.

To break down household responses to the TOU program around the peak rate period, I exploit the following DID-style spline regression model[17]:

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

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. There are three indicator variables in the model: the first indicator variable $\mathbb{1}[\text{Treatment}]_i$ has the value of 1 if household i is assigned to the treatment group; the second indicator variable $\mathbb{1}[\text{Post}]_t$ equals 1 when the day t is in the treatment period; the last indicator variable $\mathbb{1}[\text{Treatment \& Post}]_{it}$ is equal to 1 only for treatment households in the treatment period. The model also includes interaction terms between HDD-relevant

[17] Table XYZ shows point estimates that are from a nonparametric model. The U-shaped ATEs across daily HDDs substantiate the use of spline regression model.

terms and those indicator variables. In the econometric model, HDD_t means the daily heating degree days on the day t. And HDD_t^* is required to introduce nonlinearity in HDD-associated response to TOU pricing.[18] The terms α_{iw}, γ_{dw}, and δ_{mw} are household-by-half-hourly-time-window, day-of-week-by-half-hourly-time-window and month-of-year-by-half-hourly-time-window fixed effects, respectively.

The primary coefficients of interest in (3) are β_9, β_{10}, and β_{11}. The three coefficients show how much electricity consumption the households assigned to the treatment group reduced after deploying the TOU program compared to those in the control group. To be specific, β_9 demonstrates the decrease in residential electricity consumption for non-for-heating uses. Both β_{10} and β_{11} collectively mean the reductions in electricity consumed to satisfy household heating needs at given daily HDDs.

Figure 7: Breakdown of Hourly Average Treatment Effects

Using the point estimates of the three coefficients of interest provided in Table **??**, I graphically summarize the predicted reductions from each of the two sources of electricity savings in Figure 7. Regarding the savings in electricity consumption for non-temperature-control uses, which are independent of weather conditions, the figure clearly shows that the treated households significantly reduced their consumption when they were subject to the peak-hour prices. Their non-for-heating electricity consumption also decreased in both pre- and post-peak intervals, albeit relatively smaller in magnitude. The changes in temperature-control-use-associated electricity consumption occurred as well in all three intervals, but its evolving pattern over daily HDDs was quite different in each interval. Specifically, the impact of TOU pricing on residential electricity consumption for heating is U-shaped in the peak rate period, while it is salient only when daily HDDs are sufficiently large in the two off-peak intervals. In other words, from the figure, it is evident that the savings originating from for-heating-purpose household electricity consumption are a nonlinear function of daily HDDs in all three intervals.

The specification (3) is also utilized to examine, during the peak rate period, the relationship between the degree of price increases and the electricity savings. The by-tariff-group estimates of the coefficients of interest are presented in Table **??**. As shown in the table, on the whole, the savings from electricity demand for non-temperature-control uses tend to be proportional to the size of price risings in peak hours. Moreover, the marginally diminishing effects of TOU pricing, discussed in Prest (2020), seem not to be championed by my point estimates. And the two estimates associated with temperature-control-use-related electricity savings (i.e., $\hat{\beta}_{10}$ and $\hat{\beta}_{11}$) are statistically significant only for the case of the smallest price increase (i.e., the Tariff Group A). Jointly, those findings imply two points. First, household reaction to the TOU prices in peak hours

[18] Mathematically, HDD_t^* is defined as follows:

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

where $Knot$ is a reference value at which the slope of the predicted line starts to change.

differs in non-temperature- and temperature-control uses. Second, the savings from non-for-heating electricity consumption do not behave as expected from the previous study. Inspired by those implications, I formulate the resulting variations in household electricity consumption as a linear function of the magnitude of rate changes in the peak-demand hours.

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

(1. Description of household responses as a linear function of price changes)

(——————)

(1.1. Econometric model)

(1.1.1. Advantages)

(——————)

(1.2. Results)

(———)

(1.2.1. Household responses in the peak rate period)

(1.2.1.1. Non-temperature-control-related responses)

(1.2.1.2. Temperature-control-related responses)

(1.2.1.3. Aggregated responses, Link to Prest)

(———)

(1.2.2. Household responses in the pre- and post-peak intervals)

(1.2.2.1. Non-temperature-control-related responses)

(1.2.2.2. Temperature-control-related responses)

(1.2.2.3. Aggregated responses, Link to Prest)

$$\begin{aligned} kWh_{ith} \;=\; & \beta_1 HDD_t \;+\; \beta_2 HDD_t^* \;+\; \beta_3 \mathbb{1}[\text{Treatment}]_i \;+\; \beta_4 \mathbb{1}[\text{Treatment}]_i \Delta RC_i \;+\; \beta_5 HDD_t \mathbb{1}[\text{Treatment}]_i \\ & +\; \beta_6 HDD_t \mathbb{1}[\text{Treatment}]_i \Delta RC_i \;+\; \beta_7 HDD_t^* \mathbb{1}[\text{Treatment}]_i \;+\; \beta_8 HDD_t^* \mathbb{1}[\text{Treatment}]_i \Delta RC_i \\ & +\; \beta_9 \mathbb{1}[\text{Post}]_t \;+\; \beta_{10} HDD_t \mathbb{1}[\text{Post}]_t \;+\; \beta_{11} HDD_t^* \mathbb{1}[\text{Post}]_t \\ & +\; \beta_{12} \mathbb{1}[\text{Treatment \& Post}]_{it} \;+\; \beta_{13} \mathbb{1}[\text{Treatment \& Post}]_i \Delta RC_i \;+\; \beta_{14} HDD_t \mathbb{1}[\text{Treatment \& Post}]_{it} \\ & +\; \beta_{15} HDD_t \mathbb{1}[\text{Treatment \& Post}]_i \Delta RC_i \;+\; \beta_{16} HDD_t^* \mathbb{1}[\text{Treatment \& Post}]_{it} \\ & +\; \beta_{17} HDD_t^* \mathbb{1}[\text{Treatment \& Post}]_i \Delta RC_i \;+\; \alpha_{dw} \;+\; \epsilon_{ith} \end{aligned} \tag{4}$$

Table 4: Treatment Effects as a Linear Function of the Price Changes in the Peak Rate Period

Figure 8: Treatment Effects as a Linear Function of the Price Changes in the Peak Rate Period

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

4.1 Multi-Dimensional Dynamics of Household Electricity Consumption

4.1.1 Household Consumption Behavior in and near the Peak Rate Period

4.1.2 Household Consumption Behavior over Daily Heating Degree Days

4.2 Policy Implications

4.2.1 Time-Of-Use Pricing with an Additional Dynamics over Daily Heating Degree Days

4.2.2 Home Automation Technologies

5 Conclusion

(...)

A Appendixes

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