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**1 Introduction**

Many energy utilities are shifting customers onto Time-Of-Use (TOU) electricity rate structures, which have become feasible owing to the diﬀusion of renewable electricity generation capacity and smart metering technology[.](#br4)[[1]](#footnote-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 two 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 the 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. oﬀ-peak price spread varies across days. While many evaluations of TOU programs consistently document reductions in electricity consumption during peak hours, the literature often ﬁnds that households’ consumption is quite inelastic to the magnitude of the within-day price changes. Notably, [Prest](#br25) ([2020](#br25)) ﬁnds that, in a TOU pricing experiment in Ireland, households were highly insensitive to the incremental increases in the peak rate.[[2]](#footnote-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](#br25) ([2020](#br25)) 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 consume for each broad category. 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. 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]](#footnote-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 that are XYZ 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 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 temperature-control-driven electricity savings during the peak rate period increased as the magnitude of the peak price grew. Instead, there is weak evidence demonstrating that the temperature-control-driven electricity savings 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 electricity savings originating from the two channels are aggregated, the diﬀerence in the combined savings between tariﬀ groups is seemingly dampened because of the opposite correlations.[[4]](#footnote-4) Indeed, this is precisely the result discussed in [Prest](#br25) ([2020](#br25)).

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 (i.e., the pre- and post-peak hours). 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. Focusing ﬁrst on the non-temperature-control electricity consumption in the hours leading up to and following the peak rate period, I ﬁnd that the TOU prices had a spillover eﬀect on households’ demand for electricity in non-peak hours: a reduction in their non-temperature-control-driven consumption. In particular, the more considerable the peak price increase, the smaller the non-temperature-control-driven electricity savings in the non-peak hours. Furthermore, I ﬁnd no concrete 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. Jointly, in the TOU program, households reacted to the peak rate increases through not load-shifting but load-shedding.

My empirical results indicate that a diﬀerent pattern emerges for the temperature-control-driven consumption changes in the non-peak hours, while the TOU tariffs also had a spillover effect. 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 higher peak-demand-hour prices 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 the 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. Collectively, 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 savings during peak hours.

In addition to their responsiveness to TOU prices, in my empirical analysis, households’ temperature-control-driven electricity savings in the peak rate period showed a U-shaped proﬁle over daily HDDs. The nonlinearity in TOU-tariﬀ-inducing temperature-control-associated savings over households’ daily heating needs discloses a veiled feature of TOU electricity pricing: its day-varying eﬀects on residential electricity savings related to temperature-control-related consumption. Suppose that the savings obtained by adopting the TOU prices stem entirely from the non-temperature-control use of electricity. In that case, the degree of savings 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 savings 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]](#footnote-5)

The U-shaped evolving pattern of the temperature-control-driven savings over daily HDDs also implies that TOU pricing induces somewhat fewer savings on days with relatively large heating needs, on which the grid is most burdened, in turn, the most signiﬁcant electricity savings are required. This undesirable quality of TOU electricity pricing, however, can be addressed by adopting a 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 electricity savings driven by temperature-control-related consumption from disappearing. Furthermore, it produces more non-temperature-control-associated savings. In light of those ﬁndings, introducing an alternative pricing structure in which the magnitude of a peak-hour price increase is proportionally coupled to daily HDDs could create additional savings on high-heating-needs days.

To sum, the results from my empirical analysis extend the previous work by isolating temperature-control-associated electricity savings from the entire TOU-price-causing demand reductions. My results demonstrate that in and near the peak hours, the savings from each of the two diﬀerent channels of electricity consumption sensitively vary according to the magnitude of the price changes in the peak rate period. That is, in determining 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 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 the two distinct categories of electricity consumption, not in the peak rate period but around 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]](#footnote-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 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]](#footnote-7)

The households who voluntarily opt-in to the experiment were randomly assigned to control and treatment groups.[[8]](#footnote-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]](#footnote-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](#br9), 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]](#footnote-10)

Figure 1: Time-Of-Use Pricing Structures

**2.2 Description of CER Experiment Data**

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

Throughout the baseline and treatment periods, meter reads for residential participants were recorded in 30-minute intervals. The high granularity of the electricity consumption data generated from a well-designed experiment enables quantifying 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’ sociodemographic 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.[[11]](#footnote-11) 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.[[12]](#footnote-12) Moreover, among the non-electric-heating households, those with unreliable meter reads are excluded from the s[ample.](#br10)[[13]](#footnote-13) This process results in 4,096 households.

The control and treatment groups in the sample are largely balanced, as shown in Table [2](#br10). Such indiﬀerences between the two groups over many observables are consistent with previous studies examining the CER experiment dataset.[[14]](#footnote-14)

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](#br25) ([2017](#br25)) and [Prest](#br25) ([2020](#br25)), 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](#br10), 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 E´ireann, 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 [3](#br11), 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 (◦F), a normal base temperature in the United States, 60◦F is utilized to compute daily HDDs, according to [Liu and Sweeney](#br25) ([2012](#br25)). The upper part of Figure [7](#br16) 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](#br12), 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.[[15]](#footnote-15) 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 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.[[16]](#footnote-16) 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.[[17]](#footnote-17) 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.[[18]](#footnote-18) 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[.](#br13)[[19]](#footnote-19)

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:

kWhitw = βw1[Treatment & Post]it + αiw + γtw + δm + ꢀitw (1)

The term kW hitw is the electricity consumption by household i on the day t during the half-hourly time window w. The indicator variable 1[Treatment & Post]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 αiw, γtw, and δm 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 βw, representing the ATE for each 30-minute interval w, are the parameters of interest. I cluster the standard errors at the household and the day of experiment levels to correct for serial correlation.

Figure 6: Half-Hourly Average Treatment Eﬀects

Figure [6](#br14) summarizes the estimated ATEs in the form of a time proﬁle. As already demonstrated in [Prest](#br25) ([2020](#br25)), 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[.](#br14)[[20]](#footnote-20) To do so, I run the following regression for each of the four tariﬀ groups:

kWhith = βp1[Treatment & Post]it + αiw + γtw + δm + ꢀith (2)

Excepting the dependent variable and the parameter of interest, the econometric model above is the same as ([1](#br14)). Speciﬁcally, as the response variable, kW hith 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 βp 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](#br25) ([2020](#br25)): 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.

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, 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[[21]](#footnote-21):

kW hith = β1HDDt + β2HDD∗t

+ β31[Treatment]i + β4HDDt1[Treatment]i + β5HDDt\*∗1[Treatment]i

+ β61[Post]t + β7HDDt1[Post]t + β8HDDt∗1[Post]t

+ β91[Treatment & Post]it + β10HDDt1[Treatment & Post]it + β11HDDt∗1[Treatment & Post]it

+ αdw + ꢀith

(3)

Like ([2](#br14)), the dependent variable kW hith 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 1[Treatment]i has the value of 1 if household i is assigned to the treatment group; the second indicator variable 1[Post]t equals 1 when the day t is in the treatment period; the last indicator variable 1[Treatment & Post]it is equal to 1 only for treatment households in the treatment period. The model also includes interaction terms between HDD-relevant terms and those indicator variables. In the econometric model, HDDt 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.[[22]](#footnote-22) The terms αiw, γdw, and δmw 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](#br16)) are β9, β10, and β11. 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, β9 demonstrates the decrease in residential electricity consumption for non-for-heating uses. Both β10 and β11 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](#br16). 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 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](#br16)) 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](#br25) ([2020](#br25)), seem not to be championed by my point estimates. And the two estimates associated with temperature-control-use-related electricity savings (i.e., β10 and βˆ11) are statistically signiﬁcant only for the case of the smallest price increase (i.e., only for the Tariﬀ Group A). Jointly, those ﬁndings imply two points. First, household reaction to the TOU prices in peak hours 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 in the following section.

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

To fully understand how residential consumers adjust their electricity consumption behavior as a set of reactions to the price changes in and near the peak rate period under the TOU price structures, it is necessary to examine the relationship between the size of price increases in the period and the electricity savings from each of the two distinct sources for diﬀerent points in time where electricity is consumed. For that reason, I quantitatively determine the relationship by utilizing the following econometric model:

kW hith = β1HDDt + β2HDD∗

t

+ β31[Treatment]i + β41[Treatment]i∆RCi

+ β5HDDt1[Treatment]i + β6HDDt1[Treatment]i∆RCi

|  |  |  |  |
| --- | --- | --- | --- |
|  | + β7HDDt∗1[Treatment]i + β8HDDt∗1[Treatment]i∆RCi  + β91[Post]t + β10HDDt1[Post]t + β11HDDt∗1[Post]t |  | (4) |

+ β121[Treatment & Post]it + β131[Treatment & Post]i∆RCi

+ β14HDDt1[Treatment & Post]it + β15HDDt1[Treatment & Post]i∆RCi

+ β16HDDt∗1[Treatment & Post]it + β17HDDt∗1[Treatment & Post]i∆RCi + αdw + ꢀit

The model is the same with (XYZ) except for interaction terms between treatment-status-relevant indicator variables (i.e., 1[Treatment]i and 1[Treatment & Post]it) and ∆RCi, where ∆RCi 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 the TOU tariﬀs on household electricity consumption as a linear function of the amount of peak-demand-hour price changes.

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

The estimates of the six coeﬃcients of interest (i.e., from β12 to β17) presented in Table XYZ are summarized graphically in Figure XYZ. And this ﬁgure, showing estimated treatment eﬀects and predicted electricity savings for each of the three intervals, re-conﬁrms the ﬁnding of price insensitivity in [Prest](#br25) ([2020](#br25)). In the peak rate period, the non-for-heating-associated electricity savings were directly proportional to the rate changes in the period. On the contrary, at a given daily HDDs, the for-heating-related electricity savings, having HDD-varying U-shaped proﬁle, were inversely proportional to the magnitude of peak-demand-hour tariﬀ changes. As shown in the ﬁgure clearly, the diﬀerences in the predicted electricity savings over the degree of price changes are apparent when the savings stemming from the two distinct sources are examined individually. The diﬀerences, however, are seemingly dampened when the electricity savings are aggregated due to the opposite correlations. Indeed, this empirical result is consistent with the ﬁnding discussed in the previous work that households were unusually insensitive to the size of the price changes in the peak rate period.

The opposite order in estimated treatment eﬀects between the two sources of electricity savings also holds in the two-hour-length pre-peak interval, although in a contrary manner. The interval shows directly proportional savings from electricity consumption for temperature-control uses to changes in the peak rate. By contrast, the variations in non-temperature-control-related electricity consumption caused by TOU prices exhibit an inverse relationship with the price changes in the peak rate period. For the same reason, the aggregated treatment eﬀects of the TOU tariﬀs are seemingly less sensitive to prices. Note that regarding the electricity consumption for heating, the TOU tariﬀs played a role only when temperatures were suﬃciently low.

Residential consumers adjust their electricity consumption behavior during the two-hour-length post-peak period as well. As in the pre-peak interval, the savings stemming from non-for-heating-associated electricity consumption were inversely proportional to the price jumps in the peak rate period. In the case of electricity consumption for heating, the TOU program provoked additional consumption in that interval, especially on freezing days. The amount of the added for-heating-relevant household electricity consumption increased as the price variations in the peak-hour interval diminished. Therefore, the resulting treatment eﬀects (i.e., the aggregated treatment eﬀects) also agree with the ﬁnding of price insensitivity in the previous paper.

In summary, under TOU pricing, the level of price changes, not merely its existence, still matters to residential consumers. The empirical results above suggest that the opposite order in estimated treatment eﬀects between non-temperature- and temperature-control uses of electricity makes Irish households appear to violate the law of demand. In other words, due to the opposite order, their high sensitivity to the TOU prices is revealed only when household electricity consumption is disaggregated to the two distinct sources of electricity savings. 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 increases in the peak rate period.

**4 Dynamics of Household Electricity Consumption under Time-Of-**

**Use Electricity Pricing**

The results from my empirical analysis clearly indicate that under Time-Of-Use (TOU) electricity pricing, residential electricity consumption is driven by various factors, such as the timing when electricity is consumed, daily HDDs, and the magnitude of price increases in the peak rate period. In other words, within-household electricity consumption behavior shows multidimensional dynamics. Based on my empirical ﬁndings, I will discuss the dynamics in detail in the following sections. Furthermore, I will also discuss its policy implications.

**4.1 Multidimensional Dynamics of Household Electricity Consumption**

**4.1.1 Household Consumption Behavior in and near the Peak Rate Period**

Exploring participating households’ electricity consumption, following a time sequence around the peak rate period, facilitates comprehending how they adapted to the deployment of TOU electricity pricing more completely. 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 the time-varying price structure can co-occur. Because those two ways of reacting to the time-varying tariﬀ scheme reshape load curves around the peak rate period, it is natural to examine the TOU-tariﬀ-inducing electricity savings as a whole from a time-moving perspective in order to grasp the dynamics of households’ behavioral changes. In the following paragraphs, interpretations of the changes in households’ consumption behavior relevant to each of the two channels of electricity savings are followed by a policy implication suggested through them.

Regarding residential electricity demand for non-temperature-control uses, the leading reaction of the treated households to the TOU tariﬀs was to reduce their heating-irrelevant consumption around the peak rate period. As discussed, to the magnitude of the peak-hour price changes under the TOU program, the not-for-heating electricity savings were directly proportional in the peak rate period while inversely proportional in the pre- and post-peak intervals. In the case of Tariﬀ Group A, although there was almost zero price variation relative to the ﬂat rate in the before- and after-peak intervals, the amount of electricity savings for that group was nearly the same in all three intervals. Meanwhile, despite the price decreases, the remaining tariﬀ groups (maintained or) conserved their consumption in both intervals. In sum, the price changes in the peak rate period caused a spillover eﬀect in those pre- and post-peak intervals: reductions in electricity consumption for non-temperature-control uses. In other words, with respect to non-temperature-control-related electricity consumption, the households allocated to the treatment group responded to the TOU program, on the whole, not through load-shifting but load-shedding.

With respect to temperature-control-use-related household electricity consumption, Figure XYZ depicts that the treated households’ primary response to the TOU program was also load-shedding. The program caused savings in for-heating electricity use during the peak rate period, especially around moderate values of daily HDDs. In the pre-peak interval, heating-associated electricity savings only occurred on days with low temperatures. In the post-peak interval, although high daily HDDs incurred additional electricity consumption after introducing TOU tariﬀs, which might be a consequence of load-shifting or rate decline, its amount was not large enough to oﬀset, for given heating needs in a day, the savings in the preceding intervals.

Measuring the electricity savings of the households in Tariﬀ Group D relative to Tariﬀ Group A validates the load-shedding interpretations. Suppose that for the treated residential consumers, load-shifting is a primary countermeasure against the TOU program. Then residential consumers in Tariﬀ Group D, compared to those in Tariﬀ Group A, had more incentive to reallocate a portion of their electricity consumption to oﬀ-peak hours because they faced a much larger price increase in the peak rate period. So in both near-peak intervals, the savings for Tariﬀ Group D must be signiﬁcantly smaller than those for Tariﬀ Group A. However, Figure XYZ, which shows point estimates obtained by setting Tariﬀ Groups A and D as the control and treatment groups, respectively, does not demonstrate a meaningful diﬀerence between them. That is, load-shifting did not play a role in reshaping households’ load proﬁles in and near the peak rate period.

Going through the curves of the predicted savings related to temperature-control electricity use for the three intervals simultaneously but by taking account of their time sequence suggests a signiﬁcant implication of the eﬀectiveness of the TOU prices in the peak rate period. According to Figure XYZ, as the magnitude of the peak-hour price escalations increases, the temperature-control-related savings in the pre-peak interval expanded proportionally, while those in the peak rate period decreased gradually. Collectively, it is likely that a larger pre-adjustment leads to smaller reductions in electricity demand for heating during peaks, which in turn results in limited additional consumption in the post-peak interval. Considering that the TOU tariﬀs are intended to conserve electricity consumption during the peak rate period, it is inferable that fewer savings caused by too large pre-adjustment deteriorate the performance of the TOU tariﬀs.

**4.1.2 Household Consumption Behavior over Daily Heating Degree Days**

My empirical results obviously illustrate that the eﬀectiveness of the TOU tariﬀs, as measured by the amount of the induced electricity savings, nonlinearly varies with daily HDDs. As discussed, the total electricity savings caused by the deployment of TOU pricing consists of two elements: the savings from electricity consumption for non-temperature-control uses and those from electricity consumption for temperature-control uses. By deﬁnition, the savings originating from non-for-heating electricity consumption are independent of daily HDDs. Hence, the nonlinearity in the eﬀectiveness of the TOU structures is utterly attributable to the other source of electricity savings, electricity consumption for heating which Figure XYZ conﬁrms.

The nonlinear relationship between the amount of TOU-price-causing electricity savings and daily HDDs indicates an interesting characteristic of the tariﬀ structure: the day-varying eﬀects of TOU pricing on residential electricity consumption. Daily HDDs, one of the critical determinants of for-heating-relevant electricity consumption, ﬂuctuate day by day. Therefore, it is intuitive that in response to daily changing household heating needs, the total amount of TOU-price-inducing electricity savings also alters every day.

The day-varying eﬀectiveness of TOU electricity pricing suggests an implication in connection with Real-Time Pricing (RTP), a type of time-varying electricity tariﬀ structure.[[23]](#footnote-23) Contrary to TOU pricing, rates typically change hourly under RTP. So compared to TOU pricing, RTP has an advantage in reﬂecting generation costs contemporaneously. Economists, therefore, prefer RTP to TOU pricing. But because TOU-tariﬀ-inducing electricity savings covariate with daily HDDs, TOU electricity pricing can somewhat emulate the favorable feature of RTP, especially on days with moderate temperatures. For example, on typical winter days in Ireland, Tariﬀ Group A’s heating-associated electricity savings in the peak rate period were more than half of the total savings under the TOU program. In other words, the time-varying rate structure already induced substantial reductions in electricity consumption according to across-day variations in generation costs, even though there were only within-day price variations under the structure. Consequently, in that case, the additional gains obtained by switching to RTP might not be signiﬁcant as economists have expected.

**4.2 Policy Implications**

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

The U-shaped curve of temperature-control-use-associated electricity savings in the peak rate period is not a desirable feature of TOU pricing. The fundamental intention of the time-varying tariﬀ scheme is to reshape load proﬁles, especially in the peak-demand period, to avoid excessive investment in power generation capacity. So a higher amount of savings in electricity consumption for heating on freezing days (i.e., on days in which the grid is most burdened) serves the purpose of the price scheme. In light of that, the U-shaped evolving pattern of the savings over daily HDDs is unattractive because on days with high heating needs, the price structure induces even less savings 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., fewer electricity savings on days with very low temperatures). My empirical ﬁndings illustrate two important relationships between TOU-tariﬀ-inducing electricity savings and the price variations in the peak-demand hours. First, the savings from electricity consumption for non-temperature-control uses are directly proportional to the size of price increases during peaks. Second, raising the magnitude of price changes in the peak rate period somewhat inhibits heating-related electricity savings from disappearing even at a high level of daily HDDs. Those two points collectively imply that scaling up the size of rate changes in the peak rate period as daily HDDs escalate allows for achieving more considerable TOU-price-inducing savings in residential electricity consumption.

Figure XYZ depicts the predicted electricity savings under the alternative pricing scheme. (...)

**4.2.2 Home Automation Technologies**

As noted in Section XYZ, under the TOU program, households’ adjustments to their consumption behavior for temperature-control electricity use during the pre-peak hours seem to result in fewer savings in the following period (i.e., the peak rate period). In Figure XYZ, the gap in the temperature-control-related savings at given daily HDDs between the lowest and the highest peak-hour rate changes, therefore, might be understood as potentially attainable savings 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 outside temperatures, PCTs with recommended default settings for temperature-control use of electricity are highly likely to contribute to minimizing the behavioral changes before the peak rate period. Moreover, the beneﬁts obtained by utilizing the automated instruments provide legitimacy for the ongoing SEAI-oﬀering Home Energy Grants, in which heating controls are an essential part.[[24]](#footnote-24)

Conﬁning the impact of TOU prices on household electricity consumption for temperature-control uses to the peak rate period by exploiting an automation technology provides more than realizing the potential electricity savings in the period. As discussed in Section 4.1.2, TOU electricity pricing can induce substantially larger electricity savings on days when the temperatures are more extreme and the demand on the grid is higher, even though the rates under the tariﬀ structure do not vary across days. Because an automated system for heating controls causes additional savings in electricity consumption for temperature-control uses during peaks, especially on typical winter days in Ireland, the savings are comparable to those from more granular types of dynamic price schemes.

**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 and temperature-control—, 1) sensitively responded to the magnitude of the price changes 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 jumps with daily heating degree days. Second, taking a close look at the relationship between the size of the peak-hour price increases and the savings from 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, 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.

1. According to Faruqui, Hledik and Sergici (2019), a residential TOU rate is oﬀered by about 15% of all America’s utilities in 2019. [↑](#footnote-ref-1)
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.” [↑](#footnote-ref-2)
3. The CER changed its name to the Commission for Regulation of Utilities (CRU). [↑](#footnote-ref-3)
4. There were four tariﬀ groups in the CER experiment. Refer to Figure 1. [↑](#footnote-ref-4)
5. Under RTP, retail prices vary across not only hours of days but days according to contemporaneous generating costs. [↑](#footnote-ref-5)
6. The detail about the CER experiment presented hereinbelow is a summary of Commission for Energy Regulation (2011). [↑](#footnote-ref-6)
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. [↑](#footnote-ref-7)
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. [↑](#footnote-ref-8)
9. The fridge magnet and stickers outlined the timebands during which diﬀerent prices were applied. Moreover, they were tailored for each tariﬀ group. [↑](#footnote-ref-9)
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. [↑](#footnote-ref-10)
11. I exclude the observations for the ﬁrst half of the treatment period because there is no counterpart observation in the baseline period. [↑](#footnote-ref-11)
12. 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 4 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 for-heating-purpose residential electricity consumption separately. [↑](#footnote-ref-12)
13. 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. [↑](#footnote-ref-13)
14. 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). [↑](#footnote-ref-14)
15. 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. [↑](#footnote-ref-15)
16. 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. [↑](#footnote-ref-16)
17. 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. [↑](#footnote-ref-17)
18. 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 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. [↑](#footnote-ref-18)
19. 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. [↑](#footnote-ref-19)
20. 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. [↑](#footnote-ref-20)
21. Table XYZ shows point estimates that are from a nonparametric model. The U-shaped ATEs across daily HDDs substantiate the use of the DID-style spline regression model in 3. [↑](#footnote-ref-21)
22. Mathematically, HDDt∗ is deﬁned as follows:

    HDD∗t = (HDDt − Knot) × 1[HDDt > Knot],

    where Knot is a reference value at which the slope of the predicted line starts to change. [↑](#footnote-ref-22)
23. Harding and Sexton (2017) provides a detailed description of various kinds of time-varying electricity tariﬀ structures. [↑](#footnote-ref-23)
24. 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. And detailed information about Home Energy Grants is available at <https://www.seai.ie/grants/research-funding/> . [↑](#footnote-ref-24)