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Jinmahn Jo (ID#: 915528897)

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1 Introduction

Many energy utilities are shifting customers onto Time-Of-Use (TOU) electricity rate structures, which have be-

come feasible owing to the diﬀusion of renewable electricity generation capacity and smart metering technology.

Under a TOU tariﬀ structure, the pre-determined growth in peak-hour rate, which is usually invariant across

days. 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, and potentially shift some of the consumption to the lower demand hours when the cost of supplying electricity is far lower.. 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 housheolds 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 elec-

tricity price, 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](#br24) ([2020](#br24)) ﬁnds that, in a TOU pricing experiment in Ireland,households were

highly insensitive to the incremental increases in the peak rate.[1](#br4) That is, consumers seem to respond only to the existence of the within-day price changes and not the magnitude of the within-day price changes. The objective of this paper is to re-examine the TOU program evaluated by Prest to understand why the households’ aggregate consumption is so inelastic with respect to the magnitude of the within-day price changes.

To measure how sensitive residential consumers are to the size of the price variations in peak-demand hours,

I decompose their consumption changes in response to TOU tariﬀs into two distinct channels of electricity

savings instead of simply investigating the changes 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). The two categories of electricity use

) are inherently diﬀerent in timeliness—the lag

between the moment electricity is consumed to create a speciﬁc service and the point the service is actually

exploited in time. In the case of non-temperature-control-relevant electricity use, which is nearly independent

of temperature variations, the timeliness is usually high. For example, lighting service has no lag because the

service is available very the moment electricity is consumed. Electricity consumption for temperature-control

uses, by contrast, can have a longer lag. Somebody might warm up his house before the time he gets home

from work by using automation technology, like Programmable Communicating Thermostats (PCTs). In that

case, PCTs cause changes in electricity consumption across hours of the day. Due to the dissimilarity, examining

the aggregate impact of TOU pricing on household electricity consumption is evidently insuﬃcient to identify

unique consumption changes relevant to each channel. In addition to the diﬀerence in timeliness, even for a given

1This 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.”

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peak-hour price increase, induced consumption changes in for-temperature-control use of electricity on mild days

could be considerably diﬀerent from those on days with extreme temperatures. Moreover, diﬀerent implications

can be drawn depending on the share of electricity savings between the two sources. For instance, although TOU

electricity pricing only has within-day price changes, the time-varying pricing can generate sizable variations in

electricity savings across days if considerable savings come from temperature-control-related electricity use. For

those reasons, in my empirical analysis, I isolate the temperature-control-use-associated savings from the whole

by exploiting temperature variations across days.

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.[2](#br5) 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 in order to draw more universal policy implications from my empirical

results. Furthermore, instead of focusing on the peak rate period, my empirical analysis also covers intervals

near the period (i.e., two-hour-length pre- and post-peak intervals), in which the level of household electricity

consumption changed a lot. 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 consumptions changes vary with the average daily outdoor temperature, and (3) how these consumption changes vary with the magnitude of the peak period price change.

One of the most compelling ﬁndings from my empirical analysis is that in peak hours, I find the households’ non-temperature-control-driven consumption was

highly responsive to the magnitude of the peak price change. During the peak rate period, the savings from electricity

consumption for non-temperature-control purposes were directly proportional to the price increases in that

period. On the other hand, the saving related to the for-temperature-control use of electricity diminished as the

degree of the peak-hour price changes became more prominent. Interestingly, due to the opposite relationship

between demand reductions and price changes in the two channels of electricity savings, 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 sources are aggregated, the diﬀerence

in the combined savings between tariﬀ groups is seemingly dampened because of the opposite correlations.[3](#br5)

Indeed, this is precisely the result discussed in [Prest](#br24) ([2020](#br24)). In addition to such price sensitivities, as expected,

their consumption changes depended on heating needs in a day (i.e., daily HDDs) for a given price spike in the

peak rate period. To be speciﬁc, during peaks, the treatment eﬀects on household electricity consumption for

temperature-control uses showed a U-shaped proﬁle over daily HDDs, which implies that the eﬀectiveness of

2The CER changed its name to the Commission for Regulation of Utilities (CRU).3There were four tariﬀ groups in the CER experiment. Refer to XYZ.

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TOU pricing varies with daily heating needs.

The nonlinearity in TOU-tariﬀ-inducing electricity savings over households’ daily heating needs discloses

a veiled feature of TOU electricity pricing: its day-varying eﬀects on residential electricity savings. 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, illustrate that on days with moderate heating needs,

a sizable share of savings does stem from electricity use for temperature-control purposes. Consequently, even

though the TOU rates are not variable across days, the tariﬀ structures already induce substantial reductions

in electricity consumption 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.[4](#br6) In contrast, the U-shaped evolving pattern of the temperature-control-relevant

savings over daily HDDs implies that TOU pricing induces rather 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 prevents the electricity savings driven

by temperature-control-related consumption from disappearing. Furthermore, it produces more temperature-

control-associated savings. In light of those ﬁndings, introducing an alternative pricing structure in which the

magnitude of peak-hour price increases is proportionally coupled to daily HDDs might create additional savings

on high-heating-needs days.

To explore why the two different categories of consumption (temperature-control-driven and non-temperature-control-driven) respond somewhat differently to the TOU prices during the peak price hours, I examine how both types of consumption change in the non-peak-price hours – and in particular, the hours leading up to and following the peak price period. In the experiment I focus on, 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 price. Moreover, the higher the peak price the households had to pay, the lower the off-peak price they had to pay. Focusing first on the non-temperature-control consumption in the hours leading up to and following the peak period, I find evidence suggesting that larger peak price increases, and corresponding larger off-peak price decreases, cause households to shift some of their non-temperature-control consumption to the hours surrounding the peak hours. In particular, the larger the peak price increase, the smaller the non-temperature-control-driven energy savings in the non-peak hours.

In contrast, I find a different pattern emerges for the temperature-control-driven consumption changes in the non-peak hours. In particular, I find that, during the non-peak hours surrounding the peak period, temperature-control-driven electricity usage falls. Moreover, I find that these reductions in non-peak energy usage for heating get larger as the magnitude of the peak price increases. That is, households that are exposed to larger peak period prices appear to reduce their non-peak usage of heating by larger amounts. This is not indicative of load shifting (e.g., pre-heating their homes prior to the peak price period). In contrast, the results suggest that the TOU program causes a reduction in the demand for heating across the full day.

This finding described above could also contribute to the result that households’ temperature-control-driven-consumption during the peak period is largely unresponsive the magnitude of the peak price increase. For example, if households that experience large peak prices use less energy for heating in the pre-peak periods, then the homes may not be as warm going into the peak hours. Consequently, larger amounts of energy may be consumed for heating in the peak hours than otherwise would have been had absent the reduction in pre-peak heating. Effectively, households’ temperature-control-driven energy usage does appear to be responsive to the peak price. However, these responses are largely seen prior to the peak period – and as a result, make the impacts during the peak period look potentially more muted.

Even in the pre- and post-peak intervals, the households assigned to the treatment group also sensitively

adjusted their consumption behavior according to the magnitude of peak-hour price increases. In other words, the

TOU prices facilitated spillover eﬀects on households’ consumption behavior in near-peak-hour intervals, during

which they were not subject to the price raised to a pre-determined level. In both intervals, the households

reduced their electricity consumption for non-temperature-control uses in inverse proportion to the size of the

peak-rate-period price increases. In addition, with respect to their temperature-control-related consumption,

they did not respond to the TOU tariﬀs until daily HDDs were suﬃciently sizable. On days with relatively

high HDDs, the TOU tariﬀs made the residential consumers reduce their for-heating consumption in the before-

peak interval as the size of the peak-hour price changes increased. In the after-peak interval, the larger the

magnitude of the peak-hour price changes, the smaller the heating-related additional consumption. As in the

peak rate period, due to the ﬂipped correlations between induced consumption changes and peak-demand-hour

price variations in the two sources of electricity savings, the seemingly lessened responsiveness of the treated

households occurred in the oﬀ-peak intervals as well.

The estimated consumption changes allow me to infer how the treated households adapted their consumption

4Under RTP, retail prices vary across not only hours of days but days according to contemporaneous generating costs.

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behavior to the TOU program around the peak rate period. As discussed, the households’ behavioral changes

were not restricted to peak hours. Regarding the electricity consumption for non-temperature-control uses, in

lieu of relocating their peak-hour consumption to oﬀ-peak hours, the households assigned to the treatment group

in the experiment simply reduced their demand in and near the peak rate period. In other words, from the

pre-peak to the post-peak intervals, the households reacted to the price jumps in peak-demand hours through not

load-shifting but load-shedding. For temperature-control-associated electricity savings, on the other hand, the

households’ consumption changes in the pre-peak hours were likely to determine the degree of their behavioral

changes in the following periods. Speciﬁcally, the electricity savings obtained from adjustment during the

before-peak interval seemed to lead to fewer savings in the following period (i.e., the peak rate period), which in

turn brought about limited additional consumption during the after-peak interval. Those sequential behavioral

changes associated with temperature-control-related electricity use have an important policy implication: under

TOU pricing, impeding such pre-adjustment by exploiting an automation instrument, like PCTs, enables more

electricity savings during peaks.

To sum, the results from my empirical analysis extend the previous work by isolating temperature-control-

associated electricity savings from the entire TOU-pricing-causing demand reductions. My results demonstrate

that around peak hours, the savings from each of the two diﬀerent channels sensitively vary according to

the magnitude of the price changes in the peak rate period. That is, in determining household electricity

consumption, not the mere existence of price changes, prices themselves 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 the two distinct sources, 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[5](#br7)

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

5The detail about the CER experiment presented hereinbelow is a summary of [Commission for Energy Regulation](#br24) ([2011](#br24)).

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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.[6](#br8)

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

groups.[7](#br8) 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.[8](#br8) 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.[9](#br8)

6While 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.

7The 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.

8The fridge magnet and stickers outlined the timebands during which diﬀerent prices were applied. Moreover, they were tailored

for each tariﬀ group.

9A 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

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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 partic-

ipating 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 the second half

of each experiment period.[10](#br9) 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.[11](#br9) Moreover, among the non-electric-

heating households, those with unreliable meter reads are excluded from the s[ample.12](#br9) This process results in

bi-monthly bill.

10I exclude the observations for the ﬁrst half of the treatment period because there is no counterpart observation in the baseline

period.

11From 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](#br24)

[Energy Authority of Ireland](#br24) ([2022](#br24)), 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](#br11) 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.

12To 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

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4,096 households.

The control and treatment groups in the sample are largely balanced, as shown in Table [2](#br10). Such indiﬀer-

ences between the two groups over many observables are consistent with previous studies examining the CER

experiment dataset.[13](#br10)

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 in-

formation stimuli. Hence, those studies usually do not control temperature variations directly. For example, [Pon](#br24)

([2017](#br24)) and [Prest](#br24) ([2020](#br24)), 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 temper-

atures, 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

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.

13To check the balance between the control and treatment groups, [Prest](#br24) ([2020](#br24)) employs a linear probability model, while a probit

model is used in [Pon](#br24) ([2017](#br24)).

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](#br24) ([2020](#br24)) and 5.1 Addressing Self-Selection in [Pon](#br24) ([2017](#br24)).

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to ever-changing outside temperatures elaborately and instantly. Furthermore, as shown in Figure [2](#br10), their elec-

tricity 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 infor-

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](#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](#br24) ([2012](#br24)). 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](#br11), 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

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this research.[14](#br12) 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.[15](#br12) 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.[16](#br12) 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

14An 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.

15In 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.

16Because 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.

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treatment eﬀect to vary as a function of daily HDDs.[17](#br13) 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[.18](#br13)

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)

17Under 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.

18The 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](#br24) ([2011](#br24)), attritions were unlikely to be associated with the RCT. Furthermore, the

level of attritions varied only marginally across treatment status.

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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](#br24)

([2020](#br24)), 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.19](#br14) 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](#br13)).

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](#br24) ([2020):](#br24) a critical determinant

of the eﬀectiveness of TOU electricity pricing in the peak rate period is nothing more than its existence. As

19In this paper, the eﬀects of four diﬀerent information stimuli on household electricity consumption are not of interest. [Pon](#br24)

([2017](#br24)) studied the eﬀects in detail using the same datasets.

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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 elec-

tricity 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

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DID-style spline regression model[20](#br16):

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.[21](#br16) 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 elec-

tricity 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

20Table 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](#br16).

21Mathematically, 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.

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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](#br24) ([2020](#br24)), 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

ˆ

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 + ꢀith

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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](#br24) ([2020](#br24)). 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

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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 the policy implications

suggested by it.

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, according to a time sequence around the peak rate

period, facilitates comprehending how they adapted to the deployment of TOU electricity pricing precisely.

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 choose to shift it to oﬀ-peak hours in order not to be subject to the peak rate as much as

possible. In this case, the level of their net electricity consumption is maintained. Because those two ways

of reacting to the time-varying tariﬀ scheme reshape load curves around the peak rate period, it is required

to examine the TOU-tariﬀ-inducing electricity savings, as a whole, in and near the period in order to grasp

households’ behavioral changes.

Regarding residential electricity demand for non-temperature-control uses, the leading reaction of the house-

holds allocated to the treatment group to the TOU tariﬀs was to reduce their heating-irrelevant consumption

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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 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 increases, the remaining

tariﬀ groups (maintained or) conserved their consumption in both pre- and post-peak 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, 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 illustrates

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 occurred even though on days

with low temperatures only. 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 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-relevant interpretation. Let’s suppose that for the treated, load-shifting is a primary counter-

measure 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 before- and after-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.

The over-HDD load proﬁles from pre- to post-peak intervals suggest a signiﬁcant implication of the eﬀec-

tiveness of the TOU prices in the peak rate period. As shown in Figure XYZ, on days with high heating needs,

savings from for-heating-associated electricity consumption during the pre-peak hours were directly proportional

to the price increases in the peak rate period. On the contrary, the savings decreased according to the price

increases during the peak rate period. Collectively, it is likely that large pre-adjustment leads to small reductions

in electricity demand for heating during peaks, which in turn results in limited additional consumption during

the post-peak hours. Considering that the TOU tariﬀs are intended to conserve electricity consumption during

the peak rate period, less savings from too large pre-adjustment deteriorates the performance of the TOU tariﬀs.

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4.1.2 Household Consumption Behavior over Daily Heating Degree Days

My empirical results obviously show that the eﬀectiveness of the TOU tariﬀs, as measured by the magnitude 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.

The nonlinear relationship between the amount of TOU-price-causing electricity savings and daily HDDs

suggests an interesting characteristic of the tariﬀ structure: the day-varying eﬀects of TOU pricing on residential

electricity consumption. Daily HDDs, which are one of the critical determinants of for-heating-relevant saving,

vary day by day. Therefore, it is natural that in proportion 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 interesting implication in connection

with Real-Time Pricing (RTP), a type of time-varying electricity tariﬀ structure.[22](#br21) 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 extreme temperatures. For example, on typical winter

days in Ireland, Tariﬀ Group A’s heating-associated electricity savings in the peak rate period is almost half

of the total savings under the TOU program. In other words, the time-varying rate structure already induces

substantial reductions in electricity consumption according to real-time generation costs, even though there were

only within-day price variations. 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

22[Harding and Sexton](#br24) ([2017](#br24)) provides a detailed description of various kinds of time-varying electricity tariﬀ structures.

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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 with ﬂexibility in daily HDDs, alongside within-day rate variations,

could address the disadvantage of typical TOU pricing, less electricity savings on days with very low temper-

atures. My empirical ﬁndings illustrate two important dynamics in peak-hour electricity savings. First, the

savings from electricity consumption for non-temperature-control uses are directly proportional to the size of

price increases in that period. Second, raising the magnitude of price changes in the peak rate period 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 proposes an even more dynamic TOU price structure. ...

4.2.2 Home Automation Technologies

The behavioral adjustment during the pre-peak hours to temperature-control use of electricity seems to result in

less savings in the peak rate period. As noted in Section XYZ, the gap in the savings from electricity consumption

for temperature-control uses at a given daily HDDs between saving curves of the lowest and the highest rate

changes in the peak rate period illustrates attainable savings potentially. And the potential savings could be

realized by minimizing households’ pre-adjustment in the pre-peak interval. In other words, technologies that

conﬁne such behavioral changes regarding electricity consumption to the peak-demand hours may improve the

eﬀectiveness of TOU electricity pricing in the peak rate period.

5 Conclusion

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A Appendixes

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