Timing the Shift: Exploring Customer Responses to TOU Pricing

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ABSTRACT

Time-of-Use (TOU) rates encourage consumers to shift demand away from peak hours, helping utilities flatten load profiles, lower capacity needs and customer bills, and reduce reliance on expensive or emissions-intensive electricity generation. Understanding how program design features such as default enrollment or opt-in affect customer behavior is essential for utilities moving toward TOU pricing. This paper examines one utility's shift from a flat rate to a TOU rate using a randomized encouragement design to assess causal impacts on residential electricity consumption.

Approximately 10,000 customers were randomly assigned to treatment (TOU rate) and control (flat rate) groups. The evaluation leveraged interval meter data, billing records, and customer income qualification status, focusing on the summer 2024 period. Impacts were estimated using two complementary methods: a simple difference-in-differences approach to visualize average load shape changes, and a novel imputation-based difference-in-differences framework to produce accurate estimates while addressing staggered adoption.

Findings show modest shifts in electricity use that align with theoretical expectations of TOU pricing. Customers slightly reduced usage during on-peak hours and increased usage during lower-priced super off-peak periods. Estimated price elasticities were -0.026 during the on-peak period. Responsiveness was similar across income groups, although income-qualified customers exhibited somewhat larger relative changes during super off-peak hours. On average, total electricity use remained relatively unchanged with customer shifting consumption to lower-priced periods, resulting in very modest bill savings. These results suggest that while TOU pricing can influence consumption patterns, behavioral and financial impacts were limited in this early implementation.

INTRODUCTION

Electric utilities face persistent challenges in managing peak electricity demand, often relying on costly peaking power plants to meet system needs during high-load periods. Time-of-Use (TOU) rates, which adjust electricity prices based on the hour of day, offer a market-based mechanism to encourage customers to shift usage away from peak hours and toward periods when demand is lower, and the marginal cost of generation is less expensive. By aligning individual consumption decisions with system-wide efficiency goals, TOU rates aim to reduce peak load and improve grid reliability.

Historically, many utilities have utilized flat-rate pricing structures that do not reflect hourly variations in system demand or supply conditions. This static pricing approach offers little incentive for customers to adjust behavior in ways that benefit the broader electricity system. Transitioning to TOU rates represents a strategic shift toward dynamic pricing models that can foster more responsive energy use. However, the effectiveness of such rates depends not only on the design of the pricing structure itself, but also on customer awareness, flexibility, and acceptance—factors that may vary widely across demographic and income groups. To support a smoother customer experience, the TOU rate examined in this study was intentionally designed with a relatively modest peak-to-off-peak price differential. This conservative approach was intended to ease customers into time-varying pricing while minimizing the risk of unintended bill increases, maintaining revenue neutrality.

One focus of this study is income-qualified customers. In this study, income-qualified customers are defined as those who either participate in a low-income energy assistance program or have selfidentified as low-income. Most of these customers receive a usage-based discount that applies to the first 600 kilowatt-hours of electricity used each month, provided their average monthly consumption remains below 1,000 kilowatt-hours.

This study evaluates the behavioral effects of a TOU rate implemented during the summer of 2024 using a randomized encouragement design (RED). A RED is like a Randomized Controlled Trial (RCT) except that in a RED the experimental group has the option to accept or reject the treatment. Often the experimental group is referred to as an “intent to treat” group because some of the subjects assigned to the experimental group reject the treatment. In this study, acceptance was very high, so we just refer to the experimental group as the treatment or treated group. Unlike much of the existing TOU literature, which has relied on opt-in participation and thus captures the behavior of customers predisposed to respond, this study evaluates a randomized default enrollment (Faruqui, Sergici, Warner 2017).[1] This design avoids self-selection bias and strengthens the internal validity of the findings, offering a more generalizable view of how customers respond to TOU pricing. Additionally, by comparing treatment and control customers across income groups, the analysis aims to inform future rate design and deployment strategies. Customers assigned to the treatment group were notified through mailed bill inserts explaining the TOU rate and its pricing components. One insert was provided prior to their transition and another midway through the summer. Figure 1 presents this TOU pricing structure, highlighting the on-peak, off-peak, and super off-peak periods.

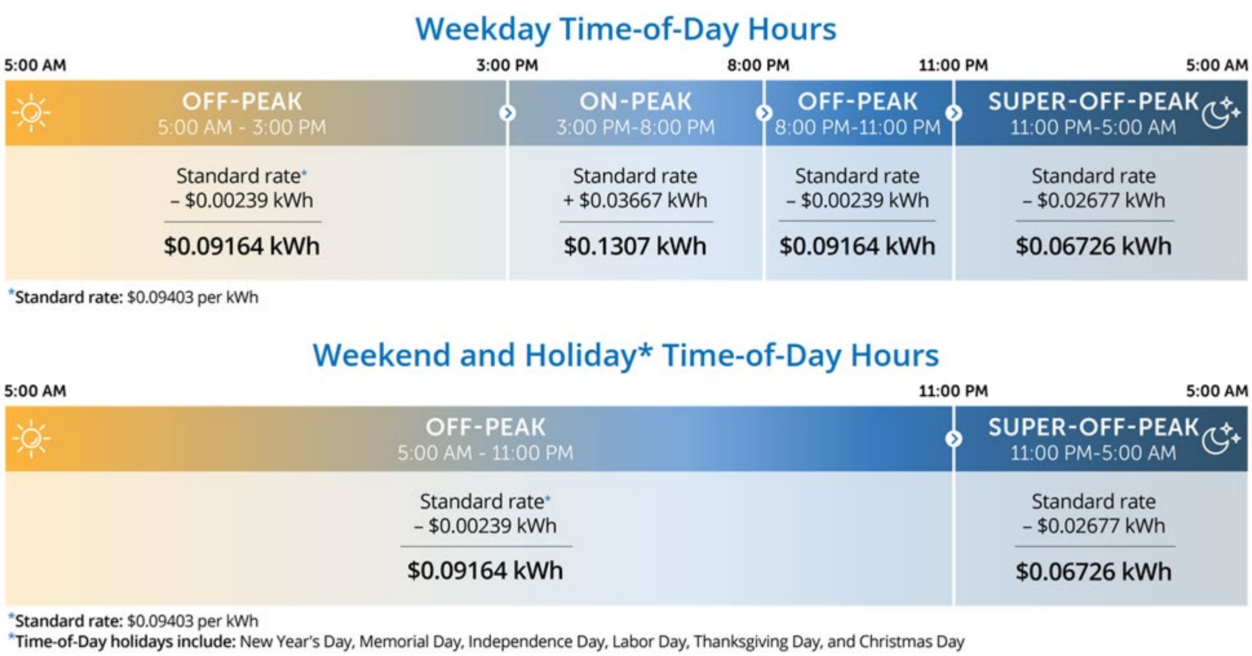

Figure 1. TOU rate structure. Source: https://www.mnpower.com/timeofday

It is important to note, based on the core billing determinants shown in Figure 1, there is a peak to super off-peak price ratio of 1.94 ($0.1307 to $0.06726) and a peak to off-peak ratio of 1.43 ($0.1307 to $0.09164). However, an important nuance to this TOU rate is the addition of fuel adjustment charges that introduce additional variable costs across the on-peak, off-peak, and super off-peak periods.

[1] Approximately 80% of the studies in the prominent meta-analysis, *Arcturus 2.0: A meta-analysis of time-varying rates for electricity*, are opt-in designs. This reflects a broader trend in the TOU literature where opt-in designs are more widely studied. Default designs, such as the one highlighted in this study, provide evidence on the behavior of the general population, as opposed to customers who are more inclined to participate.

Moreover, there is a distinct flat fuel adjustment for customers not on the TOU rate. These rates vary month-over-month and can significantly impact the overall volumetric charges that customers face.[2] Figure 2 shows the average weekday volumetric rates that customers faced under the TOU rate during the June 2024 to September 2024 analysis period. Consequently, these adjustments slightly alter the total peak to off-peak price ratios for TOU customers, changing the average peak to super off-peak ratio to 1.76 ($0.176 to $0.099) and a peak to off-peak ratio of 1.33 ($0.176 to $0.132). For the analyses presented in this study, the "all-in" price faced by customers, including the fuel adjustment charges, was used. By using the all-in price, the study aims to ensure behavioral responses reflect the actual price signals experienced by customers. Admittedly, most customers were likely unaware of the actual price signals (peak to off-peak ratios with fuel adjustment) since the rate marketing materials only highlight the variable kWh portion of the rate in Figure 1. Therefore, observed load impacts are likely due to the peak/off-peak ratios without the fuel adjustment.

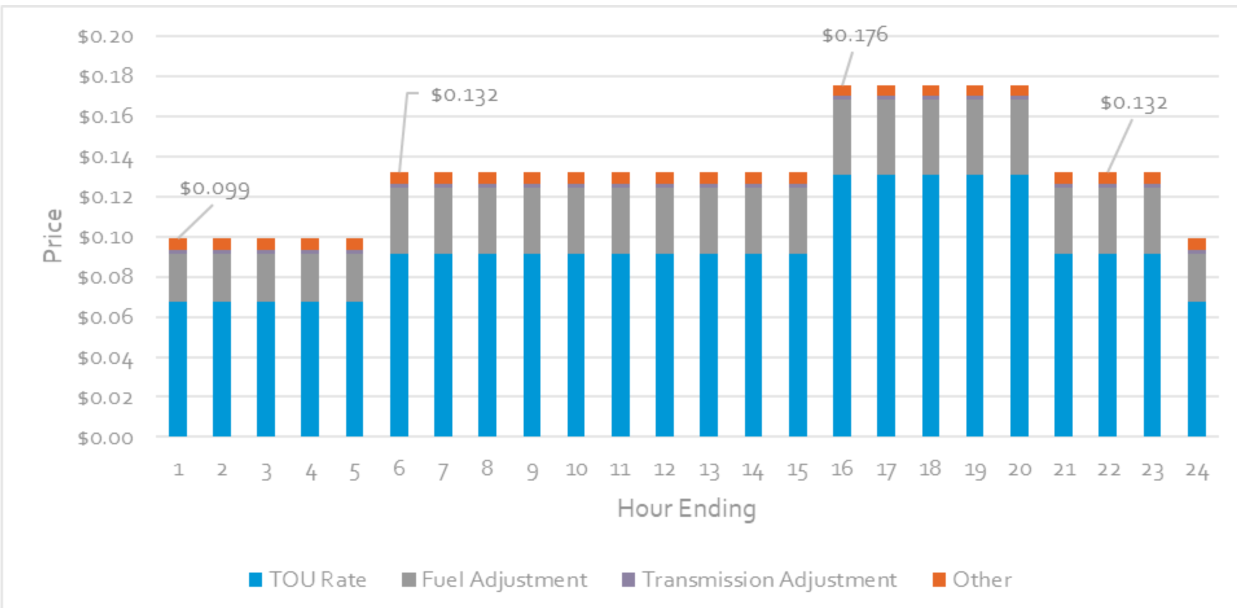

Figure 2. Weekday TOU Volumetric ($/kWh) Charges with Averaged Fuel Adders

EXPERIMENTAL DESIGN

This study employed a randomized encouragement design to allocate customers into treatment and control groups for evaluating the impacts of the rate transition. Approximately 10,000 residential customers were screened and selected based on eligibility criteria, including at least one year of historical interval meter data, the presence of a communicating interval meter, and the absence of dual-fuel systems or co-generation. These customers were randomly assigned to either the TOU rate (treatment group) or retained on the standard flat rate (control group), with each group consisting of approximately 5,000 customers. Customers were primarily notified through bill inserts, with limited use of more direct communication channels such as email. Figure 3 below illustrates the structure and timing of the rollout.

[2] Average fuel adjustments were $0.037 for on-peak, $0.033 for off-peak, $0.024 for super off-peak, and $0.034 for the flat rate.

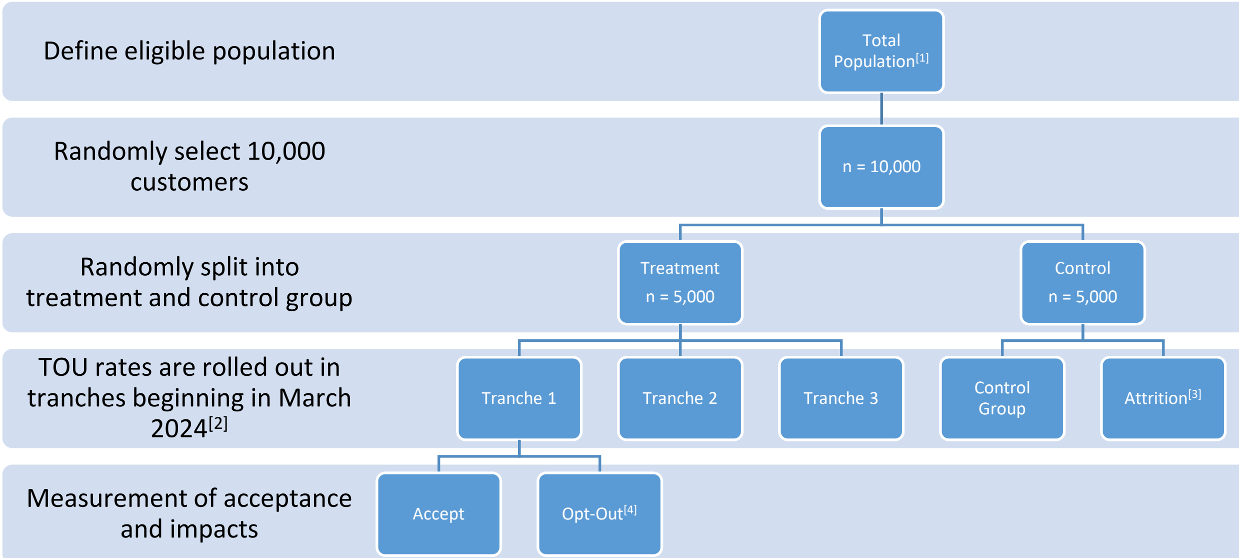

Figure 3. Experimental Design. *Notes: 1. Eligible customers were required to have a minimum of one year's billing history on the flat rate, own an interval meter with adequate communication capabilities, and have the absence of any dual fuel usage or co-generation systems. 2. The figure shows three tranches, each transitioning at different times. The true number of tranches was greater than three, with customers gradually transitioning over the course of the spring of 2024. The purpose of these panes is to illustrate that customers had variation in the timing of their transition. 3. Attrition in the control group could come from natural account closure or customers volunteering to participate in the TOU rates. 4. It is expected that there are certain customers from each tranche that will decline treatment or will eventually opt-out and transition back to the flat rate.*

This design provides a particularly strong foundation for causal inference. By randomly assigning eligible customers to treatment and control groups prior to the rate transition, the study ensures comparability across key characteristics, both observed and unobserved. Customers in the treatment group were defaulted onto the TOU rate and had the option to opt out, but in practice, nearly all accepted the assignment (only one opt-out was observed) making the effective treatment uptake rate nearly universal. However, the minimal level of attrition may reflect limited awareness of the transition, given that customers were informed primarily through bill inserts. Regardless, this structure preserves the integrity of the experimental comparison, allowing for a clear estimation of the causal impact of TOU pricing on customer behavior.

IMPACT ESTIMATION METHODOLOGY

DSA conducted the impact evaluation of the rate transition by integrating multiple data sources and modeling techniques. The analysis drew on 15-minute interval AMI data, monthly billing records, and customer-level indicators such as TOU enrollment dates and income qualification status. Interval data were aggregated to hourly values and records were consolidated using unique service and location identifiers to ensure accurate attribution across properties. The dataset underwent extensive cleaning, including deduplication, reconciliation of billed and interval energy use, and outlier detection. Each customer was flagged by their transition date and income eligibility to enable segmentation analysis. The evaluation focused on the summer period between June 1, 2024, and September 30, 2024, capturing post-transition consumption during the months when TOU pricing is expected to have the greatest impact. Impact estimation was then carried out using two complementary methods: a simple difference-in-differences approach to visualize hourly load shapes in the pre- and post-transition periods, and an imputation-based DiD framework to produce precise hourly impact estimates that account for staggered adoption and individual consumption patterns. These two methods are described in more detail below.

1. **Simple Difference-in-Differences (DiD) for Visualizing Summer Load Shapes**

To build intuitive insights into how customer load patterns shifted after transitioning to the TOU rate, DSA started with a simple DiD approach. This method compared the change in electricity consumption for the treatment group before and after treatment to the corresponding change observed in the control group over the same periods as specified below:

$$\widehat{Impact}_{d,h} = \left(Participant\ \overline{kWh}_{post,d,h} - Participant\ \overline{kWh}_{pre,d,h}\right) - \left(Control\ \overline{kWh}_{post,d,h} - Control\ \overline{kWh}_{pre,d,h}\right)$$

Where:

- The calculation is performed separately for each hour of the day (h) and day type (d) to account for variations in electricity consumption patterns by time of day and differences between weekdays and weekends/holidays.
- The first difference is the change in average hourly consumption between the pre intervention and post intervention periods for participants enrolled in TOU.
- The second difference is the change in average hourly consumption between the pre intervention and post intervention periods for the control group.
- Subtracting the second difference (control group) from the first difference (TOU participants) provides the net hourly load impact, controlling for external factors that may have influenced consumption for both groups.

This method provides an intuitive view of the treatment effect across hours, facilitating clear visualization of how the average daily load shape changed during the summer. It highlights the hourly pattern of behavioral response and serves as a useful diagnostic tool for checking the alignment of the treatment and control groups prior to the treatment period. While it does not account for staggered treatment timing, customer-specific trends, or imbalances in random assignment, it functions as a high-level tool to interpret the typical direction and shape of load changes in the post-treatment period.

2. **Imputation-Based DiD for Hourly Impact Estimation**

Building on the standard difference-in-differences framework, this section describes a modified version of DiD, designed to capture the overall impact of the TOU rollout with greater precision. Drawing on novel methods developed by Borusyak, Jaravel, and Spiess (2024), this imputation-based approach allowed DSA to estimate treatment effects while accounting for the gradual, tranche-based rollout of the TOU rate. Each tranche transitioned at a different point during spring 2024, resulting in variation in pre- and post-treatment periods across customers. This staggered timing is typical in energy conservation programs, where customer enrollment and participation often occur on a rolling basis.

Unlike the traditional DiD or two-way fixed effects models, which risk "forbidden comparisons" by implicitly comparing outcomes of newly treated customers to those already treated, the imputation approach avoids this problem by constructing individualized counterfactuals. These counterfactuals are based on both the customer's own pre-treatment trajectory and outcomes observed in the control group. By doing so, the method ensures that comparisons are only made between treated and untreated observations at the same point in time, eliminating biases that arise from overlapping treatment periods. This feature makes the approach particularly well-suited for evaluating this TOU rollout, where random assignment was combined with staggered enrollment dates. The following provides more detail on this imputation based method.

For each treated customer i at each hour t, we first predict what consumption would have looked like had the customer remained on the flat rate. Broadly, this is calculated via this concept:

$$\widehat{Y_{it}} = f_t + g_i(t)$$

Where:

- $\widehat{Y_{it}}$ represents the electricity usage customer i would have consumed at time t had they remained on the flat rate
- f_t represents the shared temporal patterns between the customer and the control group
- $g_i(t)$ reflects the treated customer's individual pre-treatment trajectory

More granularly, the counterfactual outcome $\widehat{Y_{it}}$ is estimated using a two-way fixed effects regression, fitted only to untreated observations (i.e., all control customers and the pre-treatment period of treated customers):

$$Y_{it} = \alpha + \gamma_i + \delta_t + \epsilon_{it}$$

Where:

- Y_{it} is the observed electricity usage
- γ_i is the customer fixed effect
- δ_t is the time fixed effect
- ϵ_{it} is the error term

The model is then used to generate counterfactual predictions for each treated customer during the post-treatment period based on the individual and time fixed effects:

$$\widehat{Y_{it}} = \widehat{\gamma_i} + \widehat{\delta_t}$$

Finally, the difference between the observed usage and the counterfactual gives the estimated treatment effect:

$$\widehat{\tau_{it}} = Y_{it} - \widehat{Y_{it}}$$

Where:

- $\widehat{\tau_{it}}$ is the estimated treatment effect
- Y_{it} is the observed consumption during the post-treatment period
- $\widehat{Y_{it}}$ is the estimated non-treatment outcome

This imputation based DiD method was selected for its ability to generate precise, hourly treatment effects while addressing the challenges of staggered adoption. Unlike traditional approaches that rely solely on group averages, this method constructs individualized counterfactuals by combining each treated customer's own pre-treatment summer behavior (from 2023) with trends observed among control customers who remained on the flat rate in both years. This modeling reduces dependence on the control group alone and produces more accurate estimates of what each treated customer's usage would have been had they not transitioned. The method is well-aligned with the randomized encouragement design, offering strong internal validity while accommodating the variation in treatment timing. These features allow for robust estimates of how TOU pricing influenced electricity use during the summer.

PRICE ELASTICITY OF DEMAND

To complement the impact estimation results, DSA additionally calculated price elasticities of demand. The elasticity analysis followed a three-step process. First, for each income group, the average hourly treatment effect was calculated using the imputation-based DiD method described above. These hourly impacts were paired with estimated counterfactual usage levels to compute the percent change in demand resulting from TOU participation during a given pricing period (e.g., on-peak or super off-peak). Second, DSA identified the price paid by TOU customers during each period by summing volumetric energy charges and any relevant fuel adjustment surcharges or income-qualified discounts. These observed prices were then compared to the average price paid by control group customers on the flat rate during the same period, yielding the percent change in price. Finally, price elasticity was computed using the following formula:

$$Elasticity = \frac{\%\,\Delta\, kW}{\%\Delta\; Price}$$

RESULTS

Figure 4 presents a visual summary of the TOU transition's impact using the simple DiD approach. The left pane shows the average hourly electricity consumption of treatment and control groups during the summer of 2023, before the rate change. The two groups display similar consumption patterns across the average day, indicating a strong basis for comparison. The center pane displays the same profiles for the summer of 2024, after the TOU rate had been implemented for the treatment group. While the overall load shapes remain comparable, a slight reduction in consumption is visible among treated customers during the on-peak period, suggesting the rate may be influencing behavior. The rightmost pane adjusts the 2024 comparison by subtracting the baseline differences observed in 2023. This isolates the change in usage attributable to the TOU rate, revealing a modest but noticeable decrease in peak-period consumption. While not intended to produce precise impact estimates, this figure offers a clear and intuitive view of the rate transition's initial effects, helping to motivate the use of more robust methods.

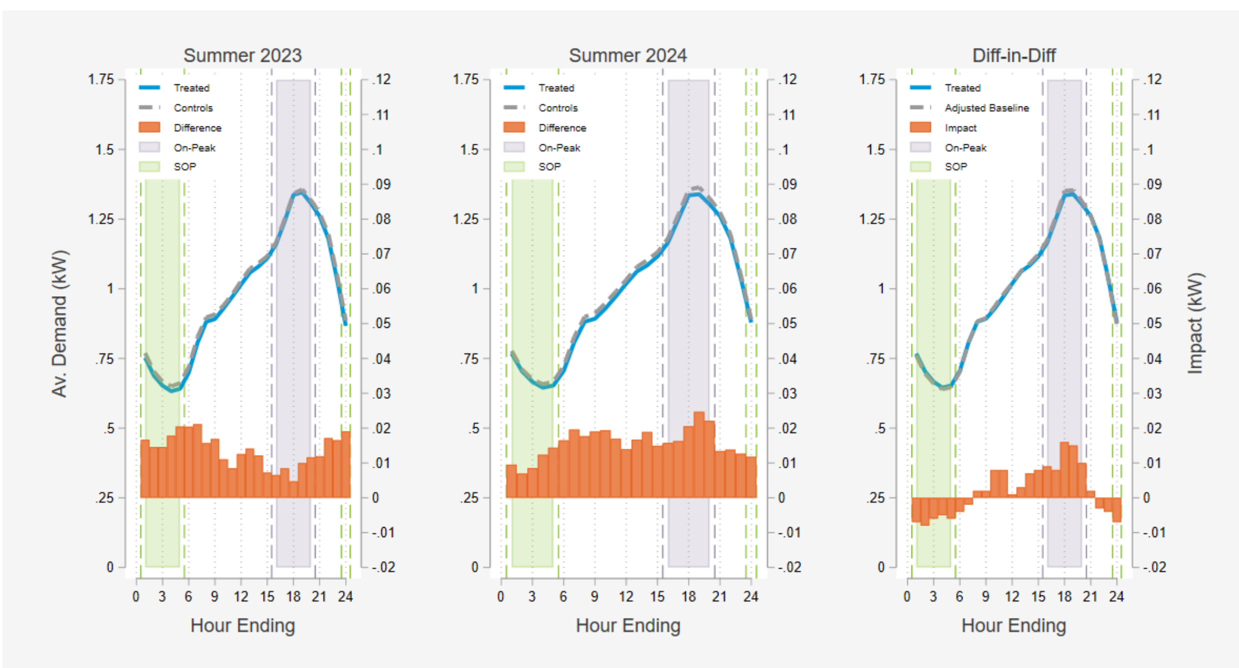

Figure 4. Difference-in-Differences for the Average Summer Weekday

Figure 5 presents the estimated hourly treatment effects from the imputation-based DiD analysis, distinguishing between weekday and weekend impacts. While the overall magnitudes of the effects are small, statistically significant differences were observed during certain on-peak hours on weekdays and during some super off-peak and off-peak hours on weekends. The direction of these changes aligns with the structure of the TOU rates, showing modest reductions in electricity use during high-priced on-peak hours and slight increases during lower-priced periods. The use of a precise estimation method was critical for identifying these effects despite their small size. The largest weekday impact occurred during the hour ending 18, with an average impact of -0.015 (90% CI: -.028 to .002) kW per customer. While this may appear minor at the individual level, such reductions can scale meaningfully. For example, a 0.015 kW decrease across 100,000 accounts would yield a 1.5 MW aggregate shift. Overall, these results suggest that while behavioral changes were limited, they were directionally consistent and potentially consequential at scale.

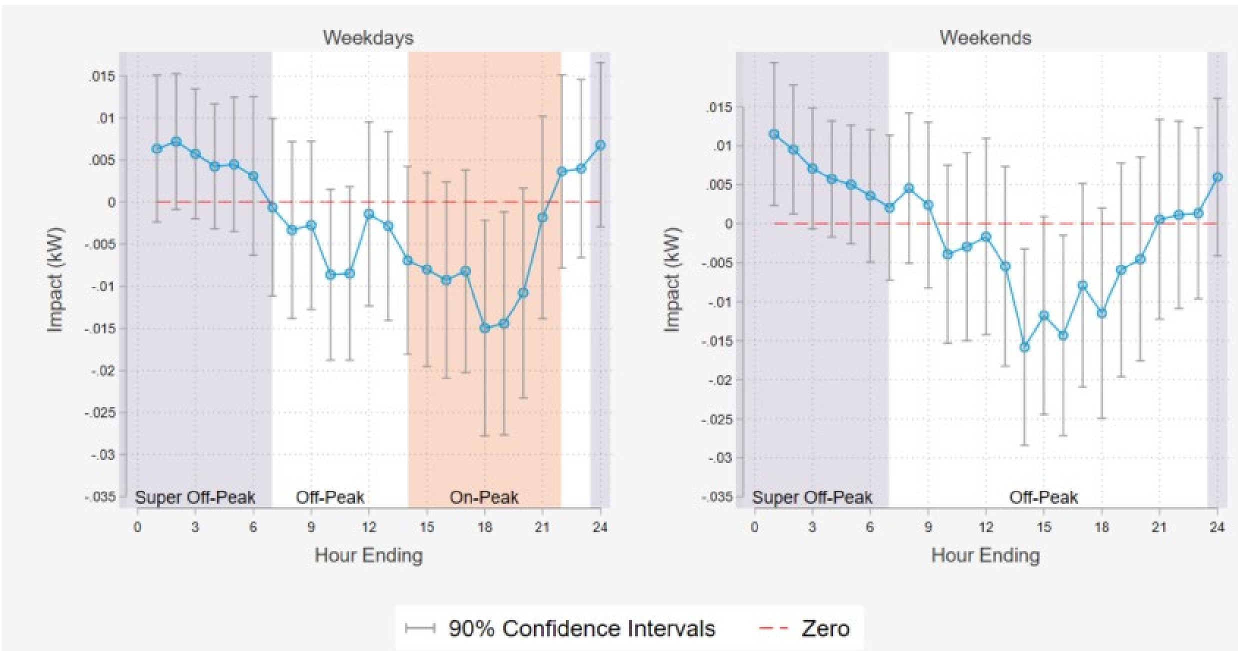

Figure 5. Weekday versus Weekend Hourly Treatment Effects

Table 1 and Table 2 summarize estimated price elasticities of demand during the on-peak and super off-peak periods, segmented by income qualification status. During the on-peak period, customers exhibited a small decrease in electricity usage in response to higher prices, with a systemwide elasticity of –0.0258. This suggests limited responsiveness overall, as a 34 percent increase in price yielded less than a 1 percent reduction in hourly demand. When broken out by income group, income-qualified customers demonstrated a slightly higher percentage reduction in consumption of -1.04% than non-income-qualified customers at -0.84%. However, the resulting elasticities were nearly identical across the two groups, at -0.026 and -0.025 respectively, indicating similarly low sensitivity to price during the peak period. These elasticities fall on the lower end of the range found in the broader literature. For example, a recent meta-analysis of time-based pricing programs estimated a weighted average own-price elasticity of -0.075, though the study noted substantial variability and uncertainty across estimates (Kahn-Lang, Palmer, Zhu, and Cappers 2025).

Table 1. On-Peak Price Elasticity by Income Status

Income Status	Sites	Average Hourly Baseline kWh	Average Hourly Observed kWh	Estimated Impact (kWh)	% Change in Demand	Base Price per kWh	Observed Price per kWh	Price Differential	% Change in Price	Price Elasticity of Demand
Not Income Qualified	4,118	1.34	1.33	-0.011	-0.84%	$0.127	$ 0.169	$0.042	33.3%	-0.025
Income Qualified	1,073	1.13	1.11	-0.012	-1.04%	$0.105	$0.147	$0.042	40.0%	-0.026
All	5,191	1.30	1.29	-0.012	-0.89%	$0.123	$0.165	$0.042	34.4%	-0.026

In contrast, super off-peak results showed slight increases in consumption across all groups in response to lower prices, though the magnitudes were small. Income-qualified customers showed a larger relative increase in usage of 1.81% compared to non-income-qualified customers at 0.26%, despite the same price decrease of 2.4 cents per kWh. The elasticity for income-qualified customers during super off-peak hours was -0.0796, a notably larger shift than that of non-income-qualified customers (-0.0139), suggesting a greater willingness or ability among income-qualified households to shift some usage to lower-priced periods. Still, overall, elasticity remained modest at -0.027, reinforcing the broader finding that TOU price signals produced only limited behavioral shifts across the customer base.

Table 2. Super Off-Peak Price Elasticity by Income Status

Income Status	Sites	Average Hourly Baseline kWh	Average Hourly Observed kWh	Estimated Impact (kWh)	% Change in Demand	Base Price per kWh	Observed Price per kWh	Price Differential	% Change in Price	Price Elasticity of Demand
Not Income Qualified	4,118	0.90	0.90	0.002	0.26%	$0.127	$0.103	-$0.024	-18.6%	-0.014
Income Qualified	1,073	0.75	0.76	0.014	1.81%	$0.105	$0.081	-$0.024	-22.7%	-0.080
All	5,191	0.87	0.87	0.005	0.52%	$0.123	$0.099	-$0.024	-19.4%	-0.027

Table 3 presents average daily values weighted by the number of weekdays and weekends within the analysis period to create a blended, daily profile. The “Flat Rate Counterfactual” denotes the daily bill calculated under a flat tariff using the baseline load, while the “TOU Counterfactual” represents charges that would have been incurred under TOU rates in the absence of behavioral adjustments. The “TOU Actual” reflects realized bills after customers responded to the TOU price signal. Average daily charges amounted to $3.044 under the flat rate counterfactual, $3.067 under the TOU counterfactual, and $3.058 under the TOU actual. The elevated TOU counterfactual indicates that, particularly during summer months when flexibility to avoid peak periods is limited, projected bills under TOU rates are higher than under a flat structure. However, since customers shifted some of their consumption to off-peak hours, slight reductions relative to the TOU counterfactual were observed.

Table 3. Typical Daily Bill Calculations

Hour	Reference kWh (A)	Observed kWh (B)	Av. Flat Rate (C)	Av. TOU Rate (D)	Flat Rate Counterfactual (A*C)	TOU Counterfactual (No Behavior Change) (A*D)	TOU Actual (with Behavior Change) (B*D)
1	0.771	0.779	$0.126	$0.092	$0.097	$0.071	$0.071
2	0.705	0.713	$0.126	$0.092	$0.089	$0.065	$0.065
3	0.667	0.674	$0.126	$0.092	$0.084	$0.061	$0.062
4	0.646	0.651	$0.126	$0.092	$0.081	$0.059	$0.060
5	0.648	0.653	$0.126	$0.092	$0.082	$0.059	$0.060
6	0.690	0.694	$0.126	$0.125	$0.087	$0.086	$0.086
7	0.778	0.779	$0.126	$0.125	$0.098	$0.097	$0.097
8	0.866	0.865	$0.126	$0.125	$0.109	$0.108	$0.108
9	0.915	0.914	$0.126	$0.125	$0.115	$0.114	$0.114
10	0.980	0.973	$0.126	$0.125	$0.123	$0.122	$0.121
11	1.033	1.026	$0.126	$0.125	$0.130	$0.129	$0.128
12	1.078	1.077	$0.126	$0.125	$0.136	$0.134	$0.134
13	1.121	1.118	$0.126	$0.125	$0.141	$0.140	$0.139
14	1.147	1.137	$0.126	$0.125	$0.144	$0.143	$0.142
15	1.174	1.165	$0.126	$0.125	$0.148	$0.146	$0.145
16	1.217	1.206	$0.126	$0.155	$0.153	$0.188	$0.186
17	1.287	1.279	$0.126	$0.155	$0.162	$0.199	$0.198
18	1.366	1.352	$0.126	$0.155	$0.172	$0.212	$0.210
19	1.364	1.352	$0.126	$0.155	$0.172	$0.212	$0.210
20	1.323	1.314	$0.126	$0.155	$0.167	$0.205	$0.204
21	1.269	1.268	$0.126	$0.125	$0.160	$0.158	$0.158
22	1.186	1.189	$0.126	$0.125	$0.149	$0.148	$0.148
23	1.042	1.045	$0.126	$0.125	$0.131	$0.130	$0.130
24	0.881	0.888	$0.126	$0.092	$0.111	$0.081	$0.081
				Daily Charge:	**$3.044**	**$3.067**	**$3.058**

CONCLUSION

This analysis provides an early look at how residential customers responded to a transition from flat to TOU pricing during the summer of 2024. The observed impacts were directionally consistent with the TOU rate structure, with modest reductions in electricity use during on-peak hours and slight increases during super off-peak hours. These results suggest that some customers adjusted their behavior in response to price signals, although the extent of this load shifting was quite limited. The overarching takeaways from this evaluation are as follows:

- TOU pricing produced small but directionally appropriate shifts in consumption. Customers slightly reduced electricity usage during on-peak hours and modestly increased usage during super off-peak periods, particularly on weekends. These behavioral patterns align with the structure of the TOU rate, suggesting that price signals did influence customer decisions, but only to a limited extent.
- By examining default enrollment under randomized assignment, this study broadens the TOU literature beyond the predominance of opt-in studies. The results suggest that while default designs avoid self-selection bias, limited customer awareness may dampen observed responsiveness, highlighting the need to pair default enrollment with proactive education and outreach.

- The imputation based DiD methodology produced statistically significant estimates for some hours, despite small treatment effects and staggered adoption. This reflects the advantages of individualized counterfactual modeling, which can enhance precision and reduce bias in the presence of complex rollout timing.
- Elasticities were low across all groups, indicating limited overall responsiveness to price. During on-peak hours, the average reduction in usage was less than 1 percent in response to a price increase of more than 30 percent, resulting in an overall elasticity of -0.0258. This suggests that, on average, customers were relatively insensitive to the price changes, and TOU pricing alone may not be sufficient to achieve meaningful peak demand reductions without additional program elements. The low elasticities may also reflect limited customer awareness, as the rate was applied by default rather than through an active opt-in process.
- Income-qualified customers exhibited slightly greater changes in demand, but their elasticities were similarly low. While income-qualified customers showed a slightly higher percentage drop in usage during on-peak hours and a somewhat stronger response to price reductions during super off-peak periods, their overall elasticities were comparable to those of non-income-qualified customers.
- On average, customers' projected bills under TOU rates would have been slightly higher than under a flat rate, particularly during summer months when opportunities to avoid peak periods were limited. However, modest load shifting reduced the overall TOU charges, partially offsetting these increases.
- Despite the introduction of time-varying pricing, most customers' usage patterns did not substantially change. This highlights the importance of supporting TOU pricing with enabling technologies (such as smart thermostats), behavioral messaging, or opt-in structures that cater to customers more capable of shifting load.
- Equity concerns remain central to TOU rate implementation. The low responsiveness among low-income households during high-priced periods suggests potential barriers to participation or flexibility that may limit the benefits these customers can realize from time-varying rates. Addressing these gaps through program design, education, or targeted incentives will be essential for achieving both grid and equity goals.

These findings offer a data-driven view of how residential customers begin to respond to time-varying price signals in practice. The modest scale of observed changes indicates that TOU pricing tends to be limited in the absence of thermostat automation, customer awareness, and substantial peak to off-peak ratios. In this case, the relatively low peak-to-off-peak price ratio was an intentional design choice aimed at easing customers onto the rate structure and minimizing the risk of adverse bill impacts. Moreover, customer outreach was limited, with only bill inserts and mail notices used to garner awareness. Regardless, the directional alignment of load shifting suggests there is underlying potential to build upon. As such, this analysis should be viewed not as an endpoint, but as a base from which to iterate and improve TOU program design.

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