

**Memo to:**

Heidi Pitts
Denine Rothman
Pablo Magallanes-Flores

Memo No:

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From:

Daniel Pike, Nathan Caron

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Prep. By:

Daniel Pike, Nathan Caron

Public Service Company of New Mexico's (PNM) Time-of-Day (TOD) Pilot Impact Analysis – 2025 Results

1 INTRODUCTION

This document provides the second set of results from DNV's Impact Analysis of PNM's TOD pilot, assessing the impacts of the TOD rate on customers and determining how much they are (or are not) reducing their load during the on-peak periods of the most recent year of the pilot, 2025. This memo will also examine the off-peak period and the whole day to determine if customers shifted their usage to these time frames or they simply reduced usage during the on-peak period.

Based on data availability and program design, the analysis focuses on two distinct time frames:

- Summer: June to August 2025
- Non-Summer: January 2025 to May 2025 and September to November 2025

For December 2025, there were complications retrieving the data. To produce preliminary results for review, we included the months listed above, with the intention of adding December data later pending availability. Besides the date range/season, we considered certain customer characteristics for the analysis. We identified customers as low-moderate income (LMI), net metered, and distributed energy resources (DER). Net metering customers made up a very small percentage of enrollees, so we excluded them from this analysis. Net metering and DER often go together for residential customers, so we also excluded DER. LMI customers had enough data provided for both the TOD rate group and the control group, so we analyzed data by LMI and non-LMI categories. During the analysis, we observed in the data customers who owned electric vehicles. Given that the rate was not primarily designed for customers with electric vehicles, and that their presence can skew the results for the customer population without EVs, we attempted to identify them based on their interval data and remove them from the analysis. This is discussed further below and in APPENDIX B.

This memo focuses primarily on the data processing approach and the results of the impact analysis.

2 DATA PREPARATION

To prepare the data, we cleaned the customer assignment list and compared it to the available interval data. The goal is to ensure the customer's original assignment in the experiment (control or rate) matches with current assignments in the billing system or that any differences are expected based on available information (e.g., known withdrawals from the program, planned transitions from control to treatment). This is particularly important for 2025 and future analyses due to planned movement of customers from the control rate to the TOD rate after completing 12 months in the control group. For those who have converted, their TOD interval data is censored at the time of conversion and not used in the analysis after that time. We hypothesized control customers might start exhibiting behavior like customers on the TOD rate as they get closer to their transition, so we examined the results at various stages relative to each control customer's transition to the rate group. These scenarios include no filtering on the control data prior to converting to the TOD rate, removing one month prior to the conversion, removing two months prior to the conversion, and removing three months prior to the conversion. The



results showed no discernible difference among the four options. As a result, no filtering was done on the control data for customers who converted to the TOD rate, ensuring as much data as possible is included in the analysis. It is still possible that certain customers in the control group adopt similar patterns of behavior to those in the rate group due to the opt-in nature of the program, but they may be doing so immediately after receipt of their meter. All participants, whether assigned to the control or rate group, wanted to participate in the rate, and they have access to the same information. The only difference between the groups is the price signal offered by the TOD rate. To see a comparison, the overall results for the summer and non-summer weekday comparisons are presented in Figure 2-1.

As mentioned in the introduction, we observed in the data customers who potentially own electric vehicles and have Level 2 chargers at their residences. (Anyone with a Level 1 charger would not have a noticeable jump in demand in their interval loads.) These customers should not have been included in the analysis and had to be excluded from the results. Of the final customer counts, 53 customers were identified as potentially owning an electric vehicle based on patterns in their interval data. 31 of those customers were in the TOD rate group and 22 were in the control group. To learn more about the method used to identify customers who potentially have electric vehicles, please see APPENDIX B.

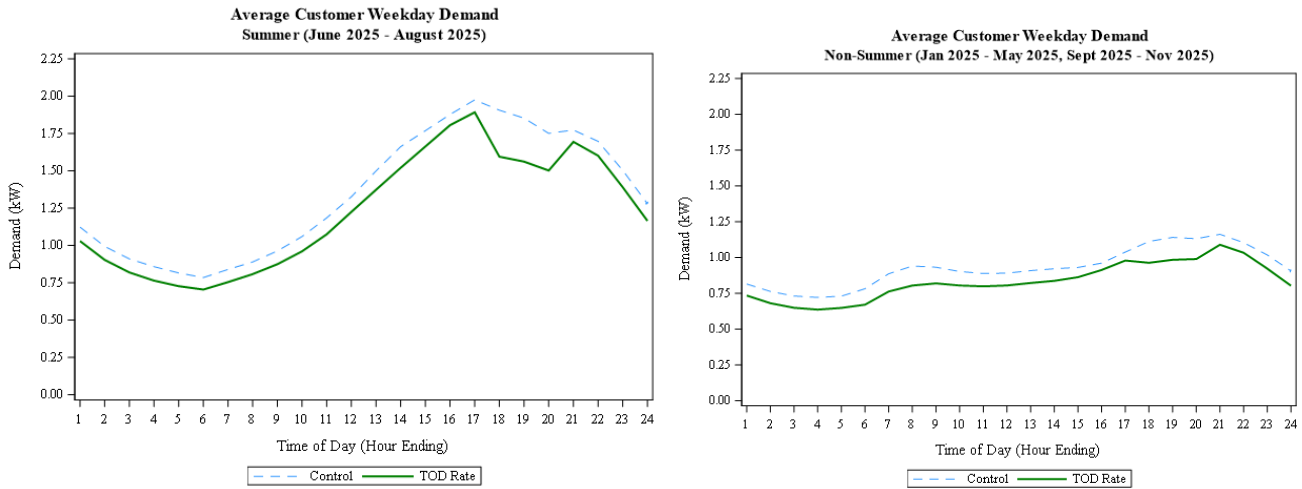
To identify LMI customers, two sources of data were provided. The first source file showed customers who were enrolled in the Low-Income Home Energy Assistance Program (LIHEAP). If they appeared in this list, they were flagged as a low-income customer. This list alone does not convey all low-income customers, however, since customers could be low-income and not enroll in this program. To attempt to identify other customers, this analysis drew on Experian income data for a large portion of the population along with the number of people at their location. This data included estimated income ranges for customers along with the estimated median income for each customer. We used the estimated median income to identify low-income customers, applying LIHEAP's eligibility rules¹ to identify additional low-income customers who were not enrolled in LIHEAP but still qualified. Any customer who did not meet either of these criteria was flagged as non-low-income.

Once these assignments were completed, we made initial comparisons of the average weekday and weekend profiles for the summer and non-summer, determining how similar the control customers' average usage was compared to the TOD rate customers' average usage after enrolment in the pilot and assignment to the treatment and control groups. Given that customers only received an interval meter after enrolment in the pilot, there is no pre-period usage available to determine how similar the groups were prior to enrolment and the treatment group taking any actions to reduce their consumption both during and outside of peak periods. Figure 2-1 presents a comparison of the average weekday shape by season, comparing the control customers to the TOD rate customers based on their collected data.

¹ <https://www.snapscreener.com/liheap/new-mexico>



Figure 2-1. Average weekday seasonal shapes by group assignment



While a reduction pattern can be seen in the TOD profile, the lack of perfect similarity outside of peak periods in both the summer and winter raises an issue. The control customers, despite random assignment, on average use slightly more energy compared to the TOD rate customers. Again, this may be due to the TOD rate customers making general energy efficiency improvements after enrolment in the rate, but we do not have pre-period data to confirm that. In the absence of that data, to conservatively estimate the reduction in load specifically during the peak periods, we needed to adjust the control profile to shift it more in line with the TOD rate profile. For the impact analysis results, we applied this adjustment to the control data. To learn more about the adjustment methodology, see APPENDIX C.

With the low-income flags assigned, the potential electric vehicle customers identified, and an adjustment applied to the control data, we assessed the load impacts.

3 IMPACT ANALYSIS

Table 3-1 contains the number of customers with available interval data broken down by season and by LMI grouping. These counts are based on the customers that were available at any given point in their time frames. The non-LMI customers make up most of the analysis, covering about 80% in both seasons. The customer counts are higher in the non-summer period as more customers joined the pilot throughout 2025. Control customers make up a smaller proportion of the totals than TOD-enrolled customers in general due to a decision to change the balance of assignments from 50/50 TOD/control in 2024 to 80/20 in 2025, to reduce program burden with a trade-off of some reduction in statistical power.

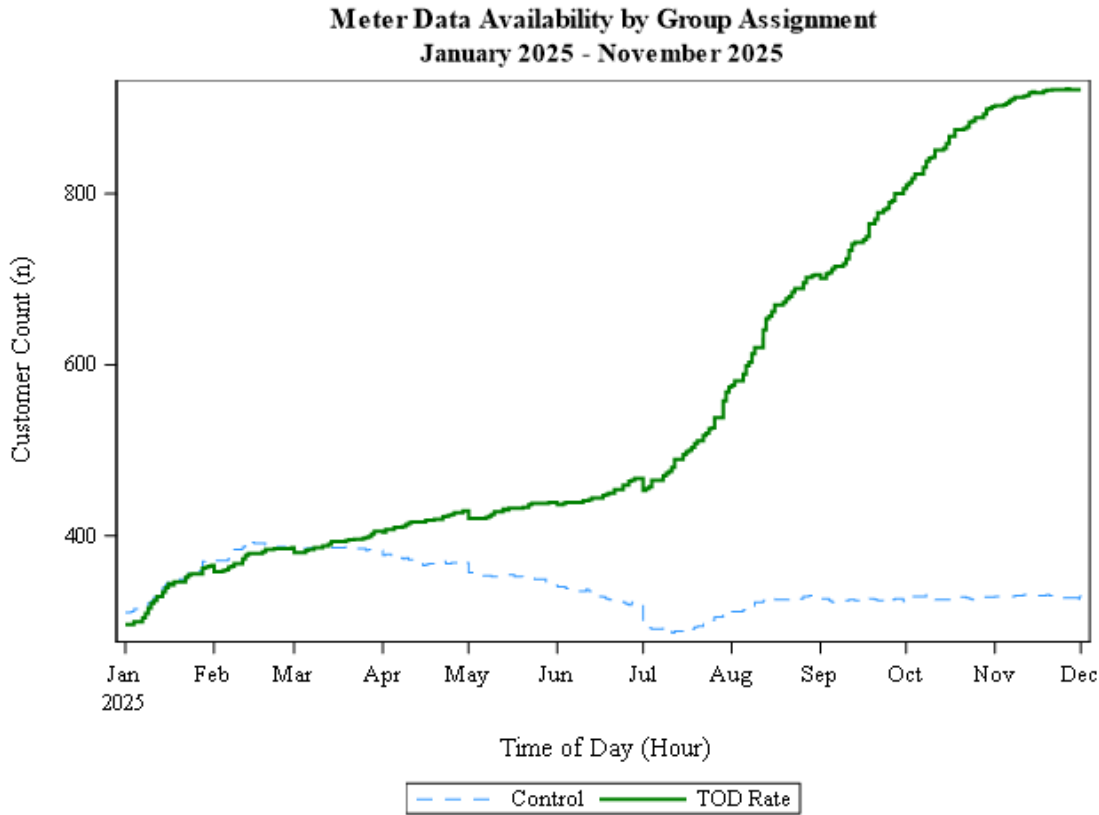
Table 3-1. Customer counts by season

Season	LMI Flag	Control	TOD Rate
Non-Summer	No	499	837
	Yes	135	216
	<i>All</i>	<i>634</i>	<i>1053</i>
Summer	No	373	621
	Yes	100	157
	<i>All</i>	<i>473</i>	<i>778</i>

When tracking this data, it is critical to ensure that the TOD data of any customer who converted to the TOD rate after being a control customer is not included in the analysis. As a result of this requirement, the control customer count dropped over

time as those customers' load data became unavailable. Figure 3-1 illustrates the data availability during 2025, showing how many meters were providing data from January 2025 to November 2025.

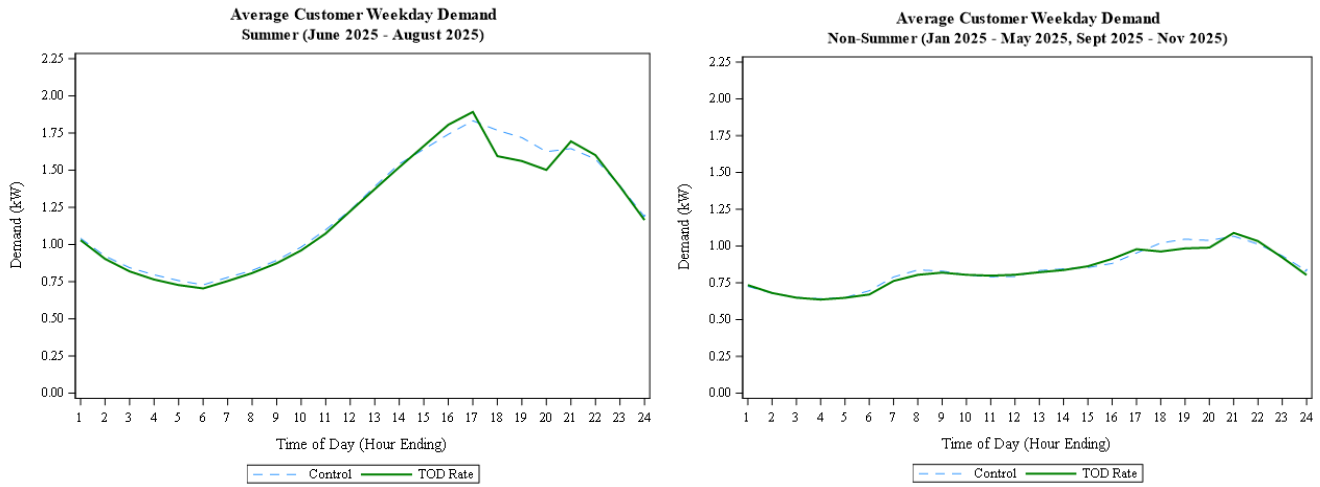
Figure 3-1. Interval meter data availability



The customer counts are based on the non-solar, non-potential EV customers included in the final analysis. Until March, the customer count is about the same between the control group and the TOD rate group. Throughout March/April, the control customer count starts to drop. This is around the time the original enrollees in the TOD pilot program who were assigned to the control group started converting to the TOD rate. While the customer count increases on the TOD rate line, this is not driven by the conversion of those customers. Once a customer converted, their interval data was removed entirely from the analysis. The TOD rate increases come only from newly assigned customers to the TOD rate group. Around July, a stronger effort was made to install more customers into the TOD rate group instead of the control group, which is why the slope of the TOD rate group increases and the control line remains about the same. This is when new control customers were added at about the same rate that original control customers were converting to the new TOD rate.

Figure 3-2 displays the average hourly weekday customer demands between the adjusted control group and the TOD rate group based on the season. For reference, the on-peak period during the summer months was 5 PM – 8 PM (hour ending 18 – 20) and the non-summer months was 5 AM – 8 AM (hour ending 6 – 8) and 5 PM – 8 PM (hour ending 18 – 20).

Figure 3-2. Average weekday customer demand by season

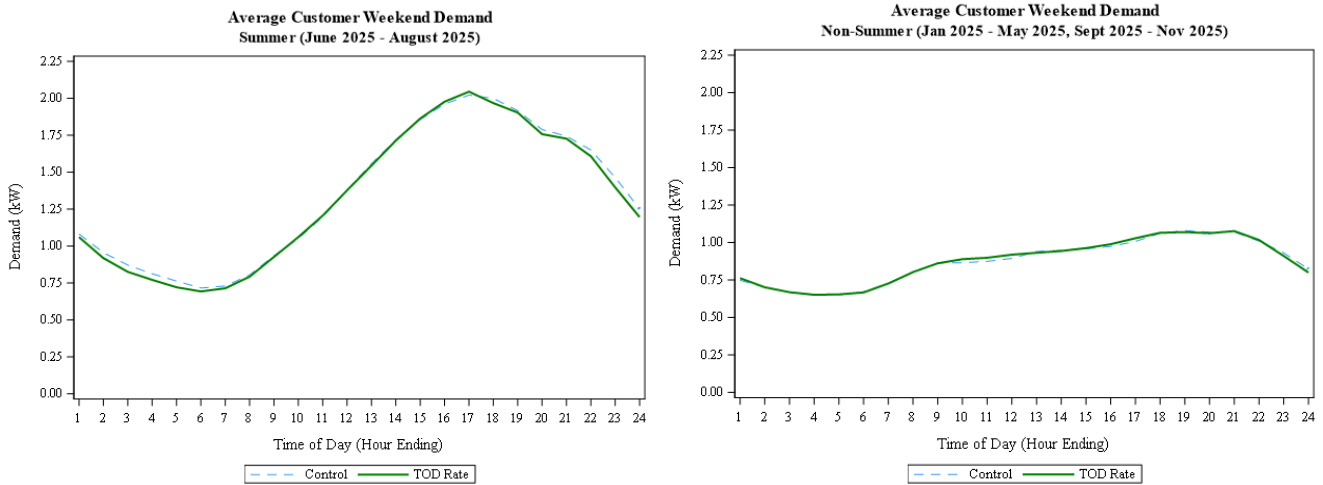


During the summer months, there is a noticeable decline in demand at the beginning of the on-peak period. The demand continues to decline throughout the three-hour window. Prior to the event, there is a slight build up in demand, indicating that the TOD rate customers likely ramped up their usage prior to the event to better prepare for reducing their demands during the event. The same can be seen after the event, with a slight bounce back as demand increases after the on-peak period. Given that the control customers have signed up for the pilot program with the knowledge they will eventually be on the TOD rate, some control customers could alter their behavior, and there does appear to be a slight reduction in their demand during the on-peak period as well, albeit not a significant one. However, even if non-significant, the control customers' tendency to reduce even a small amount of demand during this period can slightly dampen the impacts seen in the TOD rate customers.

For non-summer, there did appear to be an attempt at some reduction, but it was not significant. Like summer, the evening on-peak period continued to show a reduction, albeit not a very strong one. Also like summer, there was a very slight ramp up of demand prior to the event and a bounce back after the event. Customers, on average, had higher demands in the summer, which allowed a greater reduction during those months than during the non-summer months. Summer reductions were likely driven by the lowering of temperatures on air conditioners. For both seasons, there was a small shift of demand away from the on-peak period, but overall, customers were more likely to try to conserve energy rather than shifting their consumption to a different time frame.

The weekends did not have any on-peak periods, so we expected customer behavior to be similar across the control and TOD customers. Figure 3-3 shows the average hourly weekend customer demands between the adjusted control group and the TOD rate group based on the season.

Figure 3-3. Average weekend customer demand by season



As expected, the control group and TOD rate group lined up almost exactly, showing that when there was no cost impact by period, the customers acted similarly.

We applied a regression model to the data to quantify the magnitude of these reductions and determine if there was any statistical significance. Table 3-2 contains these results.

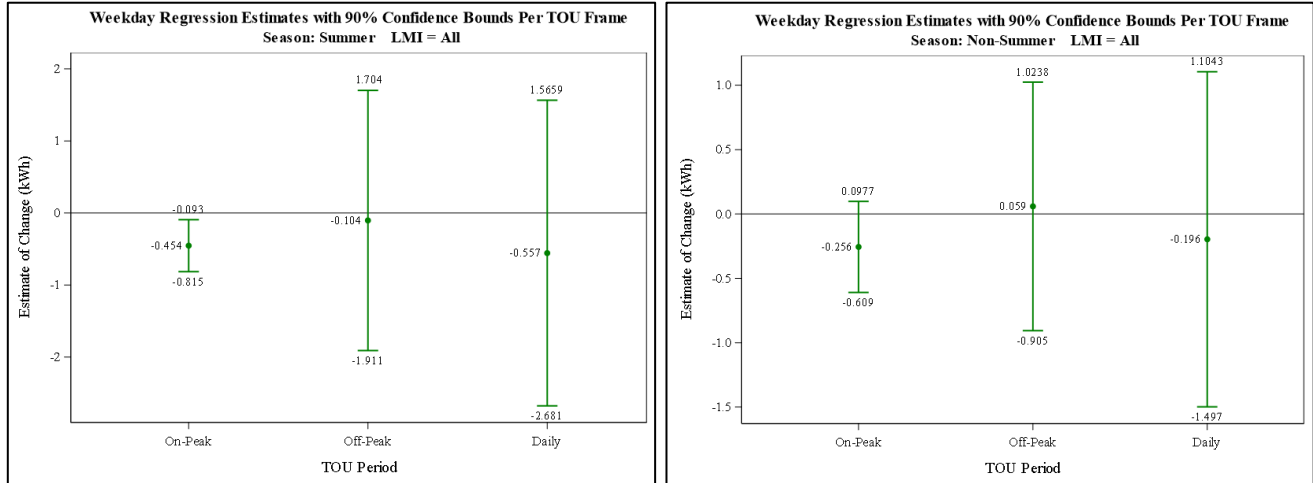
Table 3-2. Regression results by season

Period	Pre-Treatment Use		DF	Estimate of Change (kWh)			Statistical Significance				
	Daily Use	Monthly Use		Daily Change	Percent Change	Monthly Change	p-Value	90% Lower Bound	90% Upper Bound	80% Lower Bound	80% Upper Bound
Summer Residential Customers											
On-Peak (3 Hours)	5.110	109.020	1,138	-0.454	-8.9%	-9.075	0.039	-0.815	-0.093	-0.735	-0.173
Off-Peak (21 Hours)	24.845	530.021		-0.104	-0.4%	-2.073	0.925	-1.911	1.704	-1.512	1.304
Total (24 Hours)	29.955	639.041		-0.557	-1.9%	-11.147	0.666	-2.681	1.566	-2.211	1.097
Non-Summer Residential Customers											
On-Peak (6 Hours)	5.428	113.984	1,554	-0.256	-4.7%	-5.114	0.234	-0.609	0.098	-0.531	0.020
Off-Peak (18 Hours)	14.774	310.249		0.059	0.4%	1.184	0.920	-0.905	1.024	-0.692	0.811
Total (24 Hours)	20.201	424.230		-0.196	-1.0%	-3.927	0.804	-1.497	1.104	-1.210	0.817

The highlighted rows are not statistically significant at the 90% confidence level, within a 10% precision. During the summer, the on-peak period did show a significant reduction in total usage: a decrease of approximately 9%. We obtained the monthly numbers by calculating the total number of non-holiday weekdays in the summer of 2025 (64) and averaging over three months. This comes to 21.333 weekdays per month. For the non-summer, the average number of weekdays per month came to 21 weekdays. All other periods listed showed an average reduction, but none were deemed to be statistically significant. This coincides with the results shown in Figure 3-2. Customers, on average, did use more energy in the summer months compared to the non-summer months, providing a better opportunity to lower usage during the on-peak period. Due to the nature of the off-peak and overall daily usage decreasing, this is another indicator that the customers were looking to reduce their usage and not necessarily shift it. While there was a small ramp up and bounce back of demand before and after the on-peak period, it was not an impactful increase.

Figure 3-4 visualizes the results shown in Table 3-2.

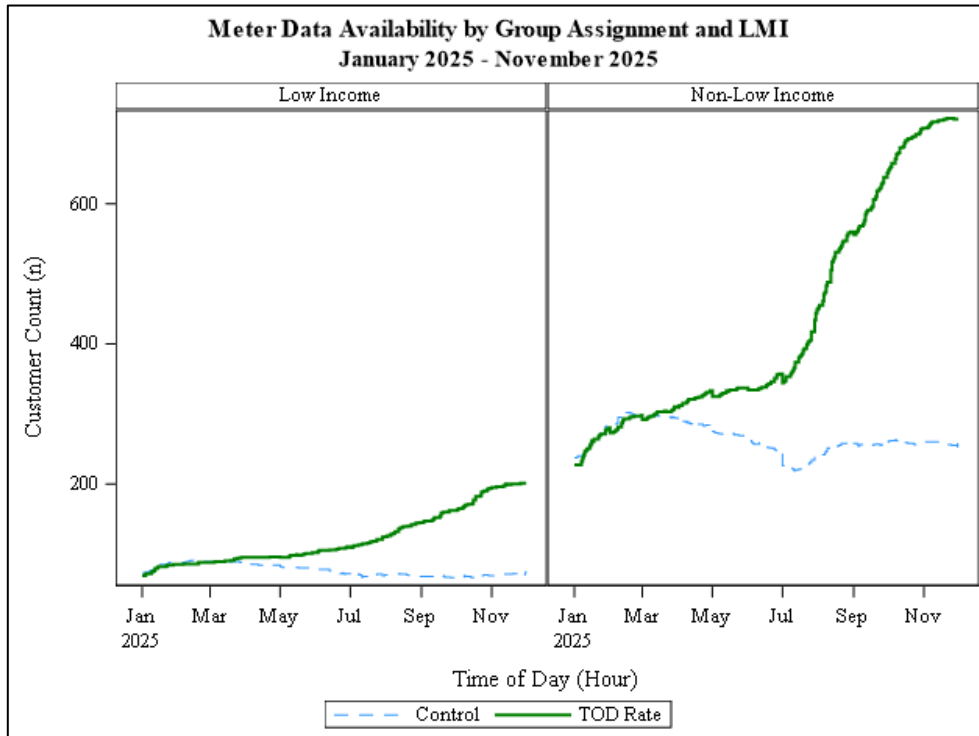
Figure 3-4. Regression plots by season



The range within the on-peak period in both seasons is much smaller, showing customers' behaviors were consistent. When the line graph is below the zero-center line for both the upper and lower bounds, it is a statistically significant decrease. The same would be true on the high side for a statistically significant increase. Any line graph that crosses the zero-center line indicates that there is no statistical significance and, therefore, there was not enough evidence to show an increase or decrease in usage compared to the control customers.

We next examined the difference between the low-income and non-low-income customer bases. Figure 3-5 shows the interval data by low-income assignments over 2025.

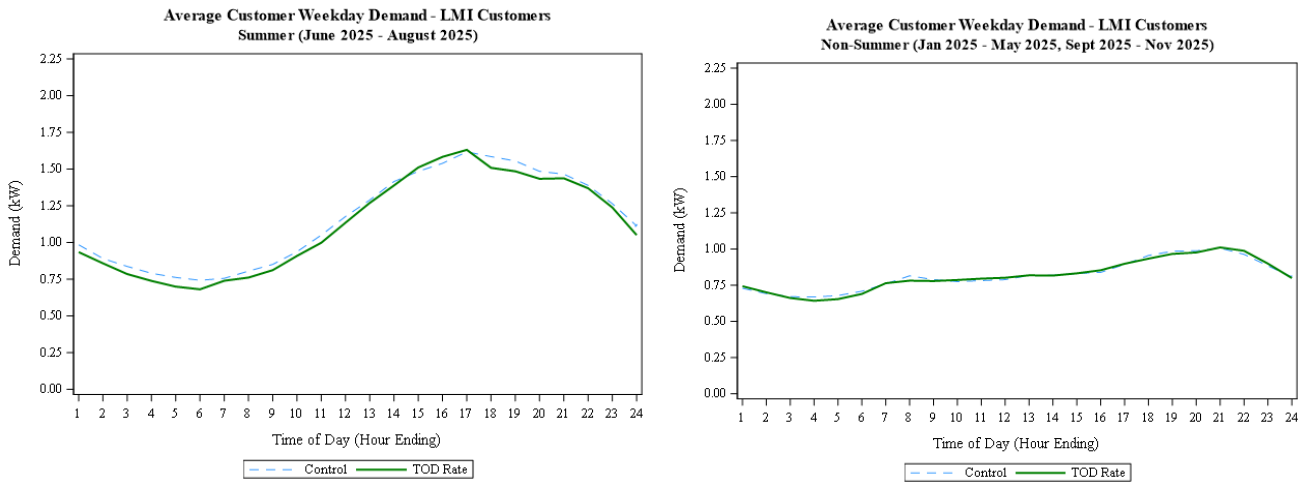
Figure 3-5. Interval meter availability by LMI assignment



Like the overall participation pattern shown in Figure 3-1, the same participation pattern was observed in the two groupings, with a large influx of TOD rate customers in the middle of 2025. The same pattern is seen for control customers as well, with a slight decline after March and then levelling out in the middle of the year. Most customers being added by summer were primarily going to the TOD rate group. That said, as seen in Table 3-1, the percentage breakdown between control and TOD rate within each group was approximately 80% non-low-income to 20% low-income.

Figure 3-6 displays the average hourly weekday customer demands between the adjusted control group and the TOD rate group based on the season for the low-income customers.

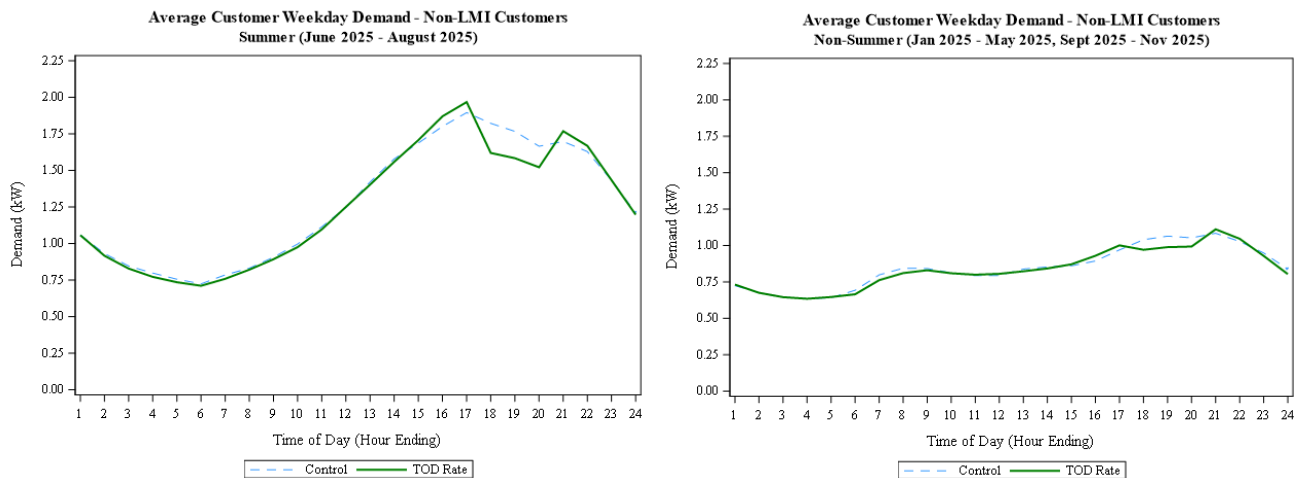
Figure 3-6. Average weekday customer demand by season – LMI customers



The summer period does show a very minor reduction during the on-peak hours. Due to there being less of a reduction, the ramp up and bounce back impacts seen in the overall sample were not as prevalent among the low-income customers. Low-income customers' demands were also lower on average than the overall customers' demands on average, which is not unexpected for low-income customers. With lower demands, it becomes more difficult to reduce that demand. Like the summer plot, the non-summer plot shows a very minor reduction, but so little that it does not look much different than the control customer demand.

Figure 3-7 displays the average hourly weekday customer demands across the adjusted control group and the TOD rate group based on the season for the non-low-income customers.

Figure 3-7. Average weekday customer demand by season – non-LMI customers



The demand reductions appeared to be more impactful for the non-low-income customers than the overall population. This was especially true during the non-summer months, during which the reduction compared to the control group appeared to be greater as compared to the overall population reduction. This showed that the non-low-income customers were the driver of the overall on-peak reductions.

Table 3-3 displays the statistical testing on the changes in usage during the peak time frames for the low-income customers.

Table 3-3. Regression results by season – LMI customers

Period	Pre-Treatment Use		DF	Estimate of Change (kWh)			Statistical Significance				
	Daily Use	Monthly Use		Daily Change	Percent Change	Monthly Change	p-Value	90% Lower Bound	90% Upper Bound	80% Lower Bound	80% Upper Bound
Summer Residential Customers											
On-Peak (3 Hours)	4.624	98.637	236	-0.198	-4.3%	-3.958	0.679	-0.986	0.590	-0.811	0.415
Off-Peak (21 Hours)	23.155	493.970		-0.631	-2.7%	-12.626	0.805	-4.851	3.588	-3.915	2.652
Total (24 Hours)	27.778	592.607		-0.829	-3.0%	-16.584	0.783	-5.790	4.131	-4.690	3.031
Non-Summer Residential Customers											
On-Peak (6 Hours)	5.210	109.416	331	-0.100	-1.9%	-2.008	0.827	-0.859	0.658	-0.691	0.490
Off-Peak (18 Hours)	14.427	302.970		0.049	0.3%	0.984	0.969	-2.068	2.167	-1.599	1.698
Total (24 Hours)	19.637	412.387		-0.051	-0.3%	-1.023	0.976	-2.907	2.805	-2.275	2.172

The highlighted rows are not statistically significant at the 90% confidence level. Summer usage showed an estimated reduction of about 4.3% during the on-peak period, albeit not statistically significant. The same is seen in the non-summer months, with a reduction of about 2%. The overall usage was shown to have reduced in both summer and non-summer months, but again not significantly

Table 3-4 displays the statistical testing on the changes in usage during the peak time frames for the non-low-income customers.

Table 3-4. Regression results by season – non-LMI customers

Period	Pre-Treatment Use		DF	Estimate of Change (kWh)			Statistical Significance				
	Daily Use	Monthly Use		Daily Change	Percent Change	Monthly Change	p-Value	90% Lower Bound	90% Upper Bound	80% Lower Bound	80% Upper Bound
Summer Residential Customers											
On-Peak (3 Hours)	5.253	112.056	901	-0.529	-10.1%	-10.587	0.032	-0.934	-0.124	-0.845	-0.214
Off-Peak (21 Hours)	25.339	540.562		0.043	0.2%	0.863	0.971	-1.939	2.025	-1.501	1.587
Total (24 Hours)	30.591	652.618		-0.486	-1.6%	-9.722	0.731	-2.813	1.841	-2.298	1.326
Non-Summer Residential Customers											
On-Peak (6 Hours)	5.491	115.308	1,222	-0.301	-5.5%	-6.026	0.214	-0.701	0.098	-0.612	0.010
Off-Peak (18 Hours)	14.874	312.357		0.059	0.4%	1.174	0.929	-1.024	1.142	-0.785	0.902
Total (24 Hours)	20.365	427.660		-0.242	-1.2%	-4.849	0.785	-1.702	1.217	-1.380	0.895

The highlighted rows are not statistically significant at the 90% confidence level. The on-peak period in the summer had a statistically significant reduction of approximately 10%. There was no increase in demand during the off-peak period, indicating that the non-low-income customers attempted to reduce energy consumption rather than shift it. There was also a 5.5% reduction in demand during the on-peak period in the non-summer months, but it was not statistically significant. Like the summer months, the demand reduction was a result of conservation, not shifting.

Figure 3-8 and Figure 3-9 visualize the results shown in Table 3-3 and Table 3-4. The reduction of the on-peak period for the non-low-income customers is the only period that was statistically significant at the 90% confidence level, showing a significant reduction in usage.

Figure 3-8. Regression plots by season – LMI customers

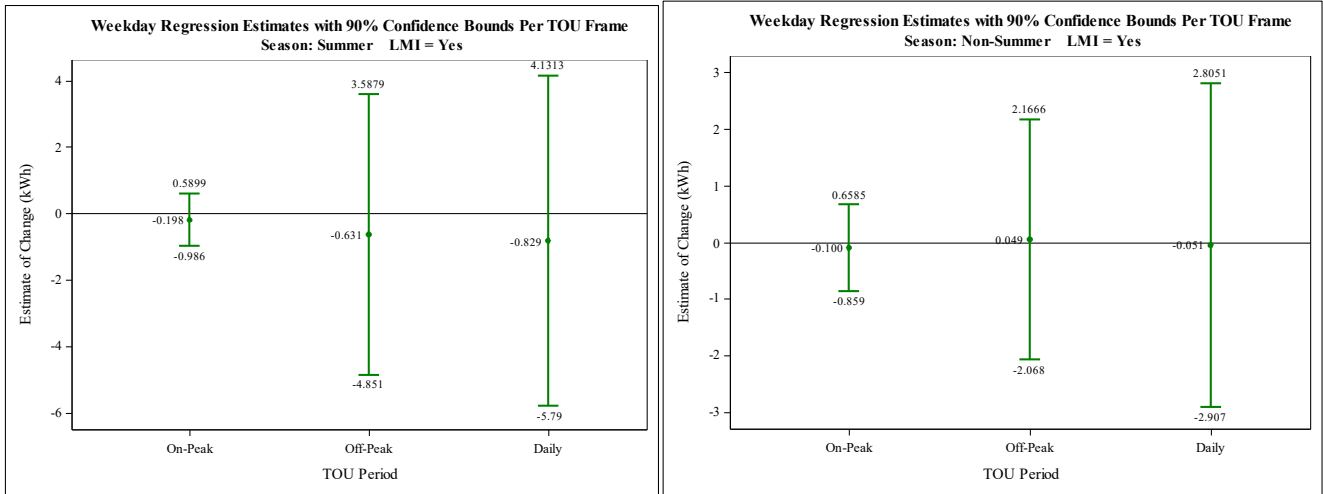
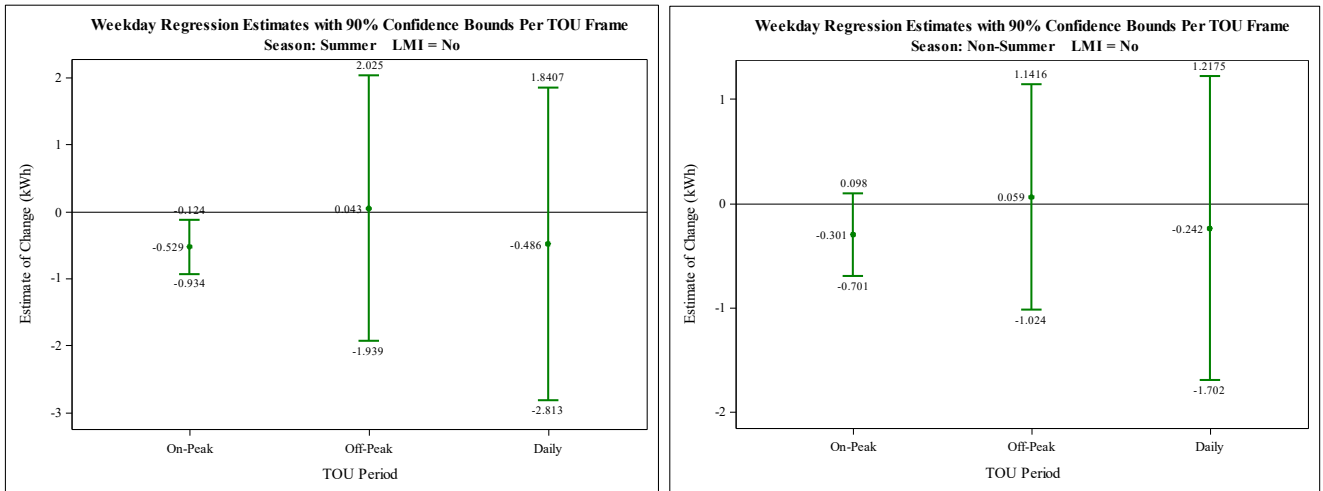


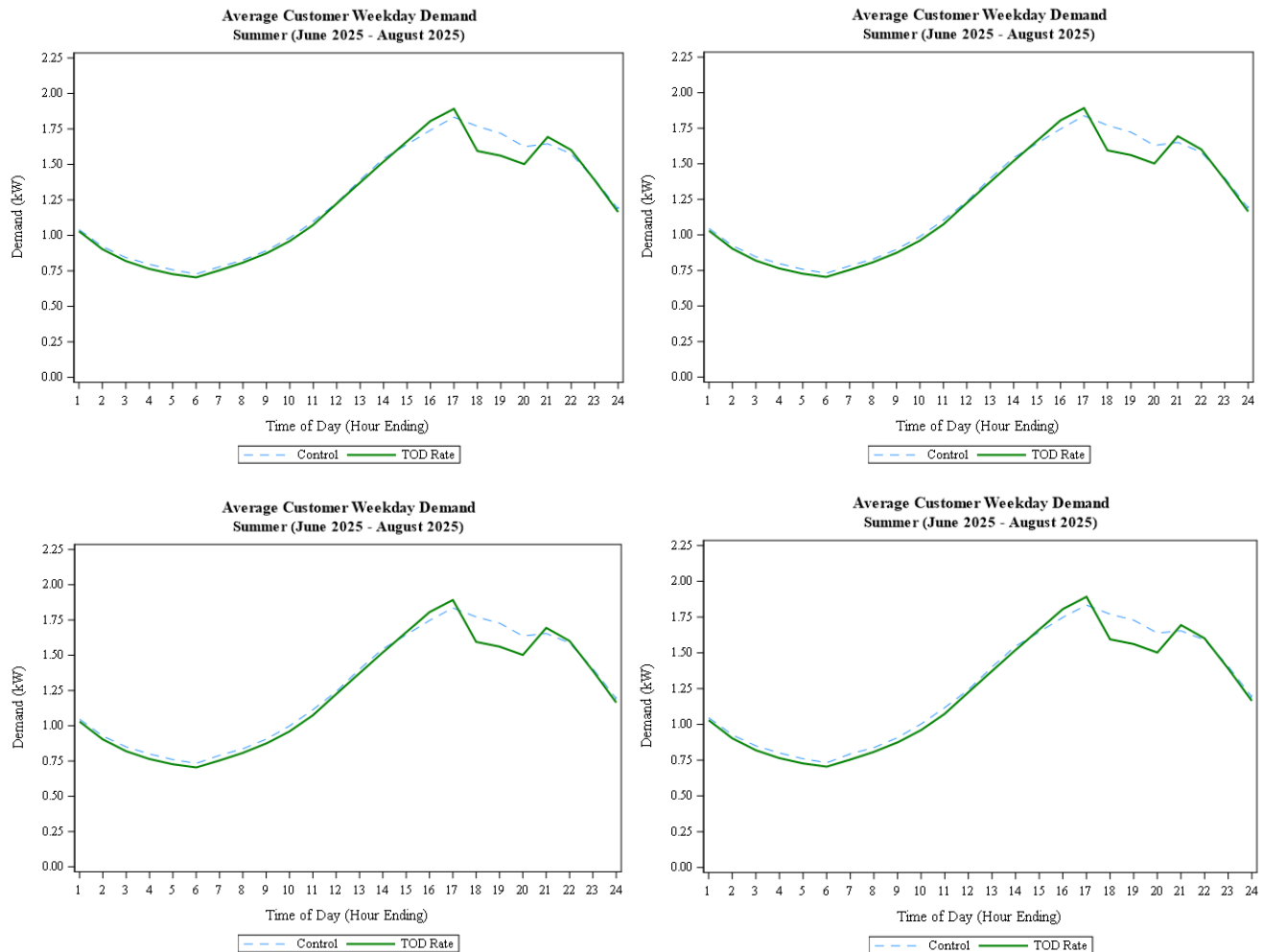
Figure 3-9. Regression plots by season – non-LMI customers



APPENDIX A. MONTH FILTERING FOR CONTROL GROUP

When preparing the data for analysis, we considered how much of an impact control group customers would have if they had started modifying their behavior as they came up on conversion date but prior to moving over to the TOD rate. If enough control customers acted like they were already on the TOD rate, their behavior could dampen the impact of the reductions in the TOD rate. While this is something that could potentially happen regardless of when a customer converts to the TOD rate, attempting to control this by filtering out a certain amount of data prior to changing rates may help limit that impact. As a result, we examined three scenarios to see if filtering out control data would have a noticeable effect: filtering out a single month of data prior to changing to the TOD rate was filtered out, filtering two months prior, and filtering out three months prior. We wanted to see if there was any change in the average adjusted control profile. Figure A-1 shows the impacts of these filtering scenarios as well as impacts without filtering. From left-to-right, top-to-bottom: no filtering, 1-month filtering, 2-months filtering, and 3-months filtering.

Figure A-1. Various filtering scenarios on the control data prior to moving to TOD rate



In each instance, there is no evident difference in the control profiles. The goal was to see if eliminating the data closest to conversion would impact the on-peak period for the control profile. In each case, the control profile still showed a tendency to reduce even a small amount of usage, enough customer actions remained in the data to show the average control customer was attempting to do even a small amount of what appeared to be reduction during the on-peak period. As a result



of this comparison, it was deemed more optimal to not filter any data from the control customer data stream to help improve accuracy in the estimates.



APPENDIX B. ELECTRIC VEHICLE IDENTIFICATION

We knew that some customers who signed up for the TOD Rate Pilot Program owned electric vehicles, which could bias the results for the rest of the population. The following section details the method we used to attempt to identify these customers so they could be filtered out of the analysis.

To identify if a customer could potentially have an electric vehicle, we needed to identify likely charging times in the interval data. Determining the charging times followed a multi-step process:

- Identifying, examining, and comparing days absent EV charging
- Conducting a lagged interval comparison looking for changes in the daily load profile

Before identifying charging in the interval data, it was important to note what type of comparison should be performed to identify charging patterns. The charger types typically available to residential customers include Level 1 (low voltage and lower demand) or Level 2 (higher voltage and higher demand) chargers. Table B-1 compares the key characteristics of these different charger types.

Table B-1. Level 1 versus Level 2 charging²

	Level 1	Level 2
Voltage	120 V AC	208 - 240 V AC
Typical Power Output	1 kW	7 kW - 19 kW
Estimated PHEV Charge Time from Empty	5 - 6 hours	1 - 2 hours
Estimated BEV Charge Time from Empty	40 - 50 hours	4 - 10 hours
Estimated Electric Range per Hour of Charging	2 - 5 miles	10 - 20 miles
Typical Locations	Home	Home, Workplace, and Public

A Level 1 charger has a voltage of 120 V AC. A Level 1 charger can be plugged into a standard household outlet. With a typical output of just 1 kW, any Level 1 charging performed by an EV will likely not be discernible when examining the whole-house load. For example, an electric dryer produces a higher power output than a Level 1 charger. This made identifying the EV pattern when examining the whole-house load more difficult, if not impossible. This is acceptable for this work as the primary goal was to identify customers who most likely had an electric vehicle so they could be filtered out. A Level 2 charger has a much higher power output, ranging between 7 and 19 kW. This is much more impactful and more readily identifiable.

In this program, customers who own electric vehicles are more likely to try to charge during off-peak hours. It has been shown that customers may be more likely to charge their cars during the evening hours or overnight hours. Also, any large increase in demands during these times is most likely going to occur because of an electric vehicle charging. We used 2 kW as a threshold to identify those customers with no charging during the time frame between 10 PM and 5 AM. If the max of these intervals was less than 2, then the day would be flagged as non-charging. This method is designed around handling

² Source: U.S. Department of Transportation (<https://www.transportation.gov/rural/ev/toolkit/ev-basics/charging-speeds>)



customers who do not typically have high demands. This method works well for these customers, whereas it was harder to determine when customers with higher demands had non-charging days.

After identifying non-charging days, we compared all days of the customer against these overnight non-charging days. For any customer who did not have enough non-EV days to represent the average day, then we combined the non-charging days with those days. Like before, these comparisons are broken down by season. If an interval had a demand that was 3 times as high as the non-EV average interval and at least 6 kW or higher, we flagged it as a charging interval.

Besides this method, we used a lagged interval approach. By comparing one interval to the next, it was easier to identify “bursts” in demand that would reflect the start of EV charging, especially with Level 2 chargers. In this method, the lag intervals were taken for each interval. If the demand increased by a certain amount from one interval to the next, we considered it the start of an EV charging session. We set this threshold to 8 kW as that is on the lower end of the expected demand output of a Level 2 charger. Because this data is considered hourly, the demand from charging started in the latter half of an hour would not be captured as well for the start of a charging session. As a result, the second lag was also considered. If the first lag increased by 4 kW and then the second lag showed an increase of 8 kW, these intervals were also considered the start of a charging session. After a charging session had been identified, each subsequent interval was compared. Once a similar decrease in demand was seen (at least 8 kW decrease in the first lag or a 4 kW decrease in the first lag and an 8 kW decrease in the second lag), we considered the charging session over. These identified charging sessions indicated if a customer potentially had an electric vehicle at their location.

Having used multiple methods to identify likely EV charging sessions, the final step was to determine which customers had enough of a charging pattern to be considered electric vehicle owners. As mentioned before, Level 1 chargers do not have any noticeable influence on a customer’s load. Also, if a customer is not charging at home, then these methods should not identify those customers. However, there is no definitive way to say these customers are not charging. We flagged as owners and then filtered out of the analysis only customers who had at least 5% of 100 or more of their intervals flagged as charging based on the methods presented with all other customers filtered out of the analysis. Using these criteria, we identified 31 TOD rate customers and 22 control customers as potential electric vehicle owners and removed them from the analysis.

APPENDIX C. CONTROL CUSTOMER ADJUSTMENT

As shown in Figure 2-1, the control customers on average had a higher demand pattern in both the summer and non-summer months than the TOD rate customers, which could result in overestimating their load reductions during peak periods. One approach to mitigating this issue is to adjust the control customer data so it is more in line with the TOD rate customer data, providing a better baseline. To calculate the adjustment factor, we needed to estimate the average control and TOD load profiles. Once the groupings were determined, we calculated the adjustment factor based on a two-hour period that began four hours prior to the start of the event. Since the evening on-peak period started at 5 PM, the two hours used for adjustment fell between 1 PM and 3 PM. We applied this adjustment factor to all hours of the day to the control customers in that group (e.g., LMI control customers in the summer months). The groupings assigned were based on the season, the day type (weekday versus weekend), and the low-income assignment. Recall that solar customers were excluded from this analysis due to their low percentage of enrolled customers. If they had been included, they would have made up another segmentation in the adjustment calculation. For the non-summer months, we used the same time frame to calculate the adjustment factor for all afternoon hours (hour-ending 1 PM to midnight). For the morning hours, the 1 AM – 3 AM window was used to calculate the adjustment factor based on the morning on-peak period. We then applied that adjustment factor back to the morning hours (hour-ending 1 AM to noon). From the average profiles, the summer adjustment factor was calculated using the following formulation:

$$Cont_adj_Factor_{Season_LMI_DayType} = \frac{(Ave_Cont_Demand_hour_{(i-4)} + Ave_Cont_Demand_hour_{i-3})}{(Ave_TOD_Demand_hour_{(i-4)} + Ave_TOD_Demand_hour_{i-3})}$$

The subscript i in the above formula represents the start of the on-peak period. For the morning on-peak time frame, i is 5 AM (HE 6), so the two hours used were 1 AM and 2 AM (HE 2 and HE 3). For the evening peaks, i is 5 PM (HE 18), so the two hours used were 1 PM and 2 PM (HE 13 and HE 14). As mentioned, the summer months used one adjustment factor for all 24 hours while the non-summer months used the afternoon adjustment factors on the afternoon intervals and used the morning adjustment factors on the morning intervals. The ratio between the control average customer usage and the TOD average customer usage was the adjustment factor. We then applied this adjustment factor back to each control customer based on what grouping they fell into. This allowed for an adjusted control baseline that was more in line with the TOD customer base before the on-peak period began. To apply the adjustment factor, we used the following formula:

$$Adj_Cont_{Season_LMI_DayType} = \frac{Cont_Cust_Data_{Season_LMI_DayType}}{Cont_adj_Factor_{Season_LMI_DayType}}$$

Using the adjusted control data, this strategy directly compared the TOD group to this adjusted comparison group. The change in load was calculated, in a regression context, using the following formulation:

$$Change\ in\ Load = (Adj_Cont_{After} - TOD_{After})$$