FINAL REPORT
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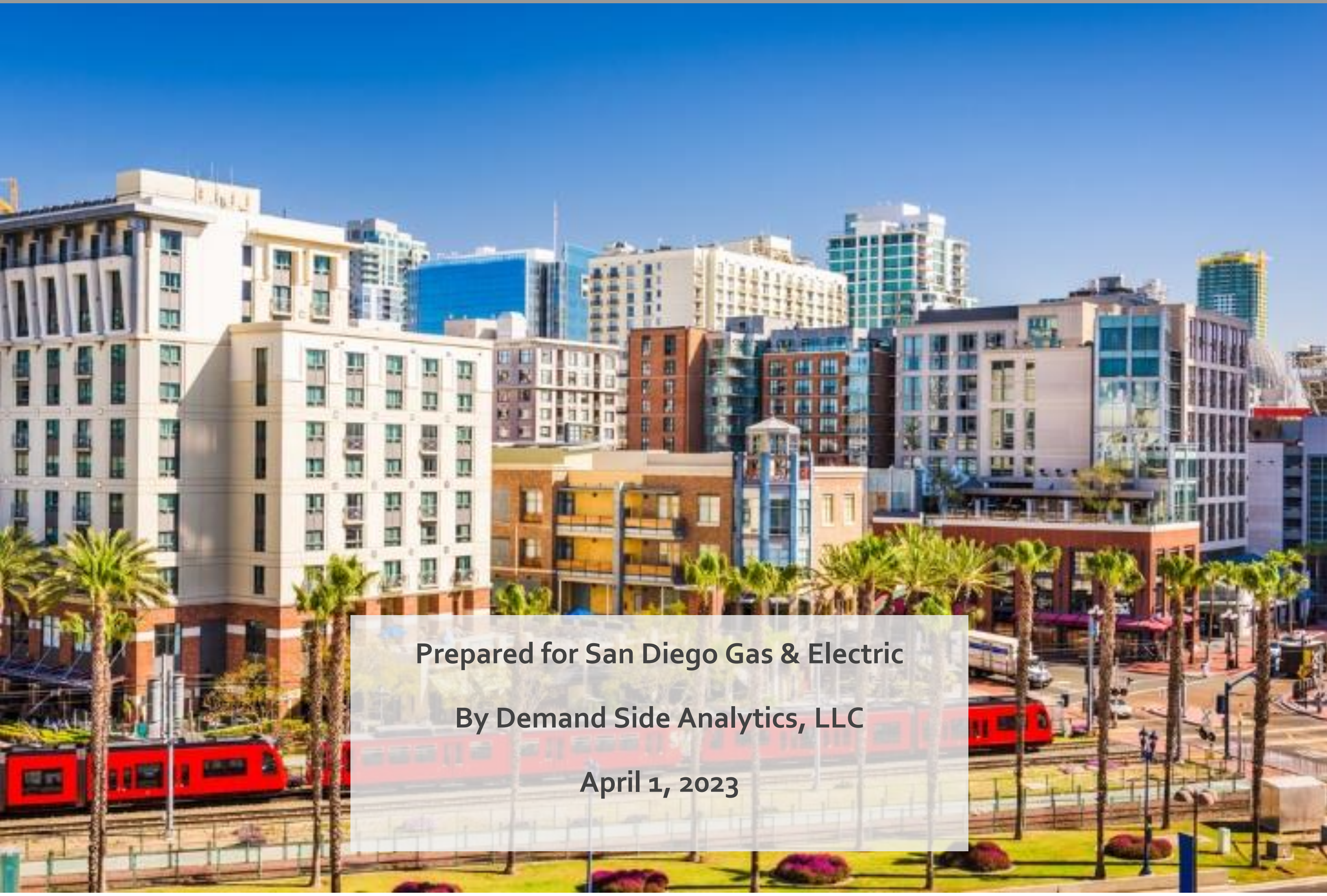
2022 Load Impact Evaluation of San Diego Gas and Electric's Electric Vehicles Time-of-Use (TOU) Rates and VGI



Prepared for San Diego Gas & Electric

By Demand Side Analytics, LLC

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ABSTRACT

This report summarizes the findings of San Diego Gas and Electric's (SDG&E) EV-TOU Rates and the Vehicle Grid Integration (VGI) rate. Over 2.8M vehicles are registered with the California DMV in SDG&E's service territory, which includes all of San Diego County and portions of Orange County. In total, SDG&E has enrolled roughly 30,000 homes on electric vehicle rates. On the top 5 load days for CAISO Gross loads, these customers curtailed demand by 16.5% (8.76 MW) on average and increased energy use during the lowest price hours. The change in load patterns coincides with the enrollment on TOU rates for electric vehicles and is sustained throughout the first year of participation. Moreover, customers delivered larger demand reductions on the highest system load days and when conditions were hotter.

In preparation for growth in electric vehicles, SDG&E deployed an infrastructure program focused on encouraging electric vehicle adoption by reducing barriers such as the expense and difficulty of installing charging equipment at multi-family dwellings (MUDs) and workplaces. Electric vehicle charging at these sites is billed under the Vehicle Grid Integration (VGI) rate, a dynamic, hourly rate that incorporates market prices, distribution cost recovery, and adders for the top 150 system load hours and top 200 distribution circuit load hours. In other words, the rates are dynamic. For sites where drivers faced dynamic prices, workplace and multi-family dwelling charging have price elasticities of -0.045 and -0.107, respectively.

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1 EXECUTIVE SUMMARY

This report summarizes the findings of San Diego Gas and Electric's (SDG&E) EV-TOU Rates and its Vehicle Grid Integration (VGI) rate. The EV-TOU rates are voluntary Time of Use rate programs structured to provide savings in electric bills for Electric Vehicle (EV) drivers while encouraging charging during times when the grid historically has more capacity. The VGI rate reacts to grid conditions in real-time and aims to provide enrolled customers with the tools necessary to respond to shifts in pricing. Both programs offer residential customers the opportunity to react daily to price signals and reduce loads when prices are high. Together, these rates aim to encourage the electrification of the transportation sector, increase access to EV adoption, and reduce the impact of electric vehicles on peak grid conditions. This report aims to provide an overview of each program's history, methods, and impacts and a summary of the Program Year 2022 ex-post and ex-ante impacts for incremental customers on San Diego Gas and Electric's (SDG&E) TOU rates for electric vehicles.

1.1 EV-TOU KEY FINDINGS

SDG&E has two main rates for electric vehicles: EV-TOU2 and EV-TOU5. In addition, SDG&E has a small number of homes on an electric vehicle rate with sub-metering for the charger, which is not included in the evaluation. On 2022 high load days, SDG&E had over 31,000 homes enrolled across the two electric vehicle rates. Table 1 shows participants' aggregate and average load impact during the top 5, 10, and 20 load days for CAISO Gross Loads, CAISO Net Loads, and SDG&E Gross Loads. On the top 5 load days for CAISO Gross loads, participant loads peaked at 53.1 MW, and participants curtailed demand by 8.76 MW on average. For the top 5 load days for SDG&E Gross loads, participant loads peaked at 56.8 MW, and participants curtailed demand by 8.02 MW on average.

Table 1: Ex-post Load Impacts on Highest System Load Days (4-9 pm)

						Avg. Customer (kW)				
System	Month	Sample[1]	New Accts	Total Accts	Daily Avg. Temp[2]	Reference Load	Load Reduction	% Reduction	New Load Impact (MW)	Total Load Impact (MW)
CAISO Gross Loads	Top 05 load day(s)	791	5,533	31,351	75.6	1.69	0.28	16.5%	1.55	8.76
	Top 10 load day(s)	791	5,533	31,351	75.8	1.64	0.26	16.0%	1.46	8.27
	Top 20 load day(s)	791	5,533	31,351	75.1	1.55	0.25	15.9%	1.36	7.72
CAISO Net Loads	Top 05 load day(s)	791	5,533	31,351	75.8	1.70	0.26	15.1%	1.42	8.03
	Top 10 load day(s)	791	5,533	31,351	74.9	1.58	0.26	16.4%	1.44	8.14
	Top 20 load day(s)	791	5,533	31,351	74.4	1.55	0.27	17.3%	1.48	8.39
SDG&E Gross Loads	Top 05 load day(s)	791	5,533	31,351	77.7	1.81	0.26	14.1%	1.41	8.02
	Top 10 load day(s)	791	5,533	31,351	75.1	1.73	0.25	14.2%	1.36	7.73
	Top 20 load day(s)	791	5,533	31,351	75.4	1.69	0.25	15.1%	1.41	7.97

[1] Estimating sample is lower than populations because it excludes sites that whose transition to EV TOU coincided with the arrival of the electric vehicle or with solar or battery installation.
[2] Participant weighted average temperature. SDG&E maps all customers to eight distinct weather stations.

1.2 VGI KEY FINDINGS

SDG&E has installed 2,611 ports at 211 sites across multi-family dwellings in its service territory. The pricing at the electric vehicle charging stations is dynamic and reflects the day-ahead CAISO market prices in addition to adders for time periods when the California grid is stressed or the local distribution grid nears peaking conditions. Table 2 summarizes the key findings.

Table 2: Summary of VGIT Key Findings

Topic	Findings
Do customer shift or reduce loads in response to the real time prices?	Customers who had to pay the real time prices reduced demand during higher prices hours. The reductions during higher priced hours were evident whether high priced period are treated as events or if the focus in estimating the price elasticities.
Did performance differ by for work places and multi-unit dwellings?	At both Workplaces and Multi-Unit Dwellings Drivers enrolled in rate to driver billing program decreased their overall charging during peak hours
Did performance differ based on customer billing types (Rate to Driver vs. Rate to Host)?	Alternatively, on rate to host billing at workplace sites, drivers would increase their overall charging when prices were higher, taking advantage of the free energy

2 INTRODUCTION AND BACKGROUND

This report presents the results of the program year for SDG&E's electric vehicle time-of-use rates (EV TOU) and the Vehicle Grid Integration (VGI) rates. Both programs are designed to encourage the electrification of the transportation sector, reduce barriers to EV adoption, reduce greenhouse gas (GHG) emissions, and encourage customers to reduce demand during peak hours and charge during hours when energy is more abundant and less costly. The report has two primary objectives: to estimate the demand reductions that were delivered in 2022 and to quantify the magnitude of incremental demand reductions during peaking conditions for use in planning.

Time of use rates and dynamic rates are considered a passive form of load management. They encourage customers to shift their use from higher-priced periods to lower-cost periods but do not directly control the charging behavior of customers or vehicles. The evaluation includes two main interventions:

- **Electric Vehicle Time of Use rates.** Due to legacy reasons, SDG&E has two primary TOU rates for electric vehicles, EVTOU2 and EVTOU5, both of which are whole-home rates. SDG&E also has a small number of homes with a sub-meter for the electric vehicle charger, which are not included in the evaluation. Nearly all new enrollments are on the EVTOU5 rate. All of the rates include a peak period from 4-9 pm, super off-peak rates from 12-6 am, and off-peak rates in all other hours. The main differences between the two whole premise rates are in the super off-peak rates, the monthly billing fee, and rates during weekends. Overall the EVTOU5 rate has a lower super-off peak price, a higher monthly fixed charge, and the same rates for weekdays and weekends.
- **Vehicle Grid Integration Rate.** The Pilot was designed to reduce greenhouse gas ("GHG") and pollutant emissions, increase adoption of electrical vehicles ("EVs"), and integrate EV charging with the electric grid through a day-ahead hourly electric rate. The Commission authorized SDG&E to install Level 2 charging stations through the Pilot at workplaces and multi-unit dwellings ("MUDs") such as apartments and condominiums. SDG&E installed, owns, and maintains 2,611 charging ports at 211 locations. The VGI pilot offers a unique Rate-to-Driver billing option where drivers' charging costs appear directly on their SDG&E bill. The rate only applies to the charging of the EV. It also relies on a unique dynamic rate, which consists of five main components:
  - ✓ The Commodity Rate component reflects day-ahead hourly market prices. This is based on the California Independent System Operator (CAISO) day-ahead market price for energy supply.
  - ✓ The base delivery component. The delivery component is designed to reflect the costs of the transportation system used to deliver energy from where it is used to where it is consumed. The electricity transportation infrastructure is referred to as the transmission and distribution (T&D) system. It includes the transmission lines, distribution lines, substations to step power up or down, capacitors to ensure steady voltage, pole top (or pad mount) transformers, and the service lines that ultimately connect to homes and

businesses. The infrastructure costs are largely sunk costs, and the rates are designed to recover the costs over time.

- ✓ A system adder that targets the top 150 system load hours (based on CAISO demand) to reflect the costs of generation capacity, which is needed to meet peak demand levels.
- ✓ A distribution rate adder or circuit adder targets the top 200 load hours of the distribution circuits that the charger is on. The adder is designed to encourage less charging when distribution circuits peak and thereby reduces the risk of overloads and the need for distribution system upgrades.
- ✓ An excess supply adder. The excess supply adder is a discount to reflect times when the grid has over-generation and insufficient loads to absorb the supply.

The remainder of this section provides context and additional detail about the EVTOU5 and EVTOU2 rates and VGI rate. In specific, it details the key research questions, summarizes 2022 grid conditions, discusses the electric vehicle TOU rates and historical participation, presents the Vehicle Grid Integration participation and rates, and documents the role of the COVID pandemic on the analysis and electric vehicle charging patterns.

2.1 RESEARCH QUESTIONS

While each program/rate at each utility has unique characteristics, the core research questions are similar:

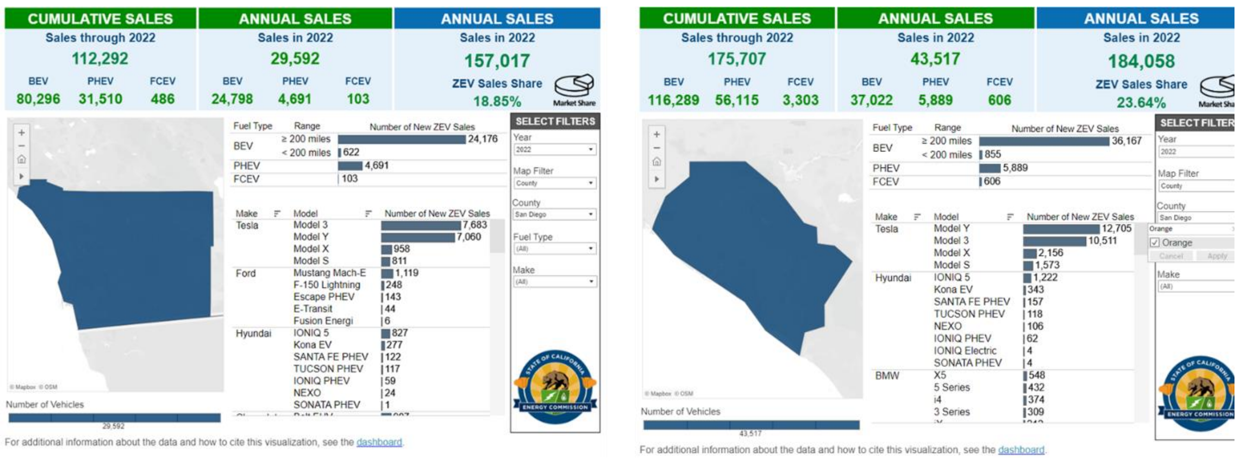
- What were the demand reductions due to electric vehicle time of use and Vehicle Grid Integration rates?
- How do load impacts differ for different types of customers?
- How does weather influence the magnitude of demand response, if at all?
- How does price influence the magnitude of demand response?
- What is the ex-ante load reduction capability for 1-in-2 and 1-in-10 weather conditions? And how well do these reductions align with ex-post results and prior ex-ante forecasts?
- What concrete steps can be undertaken to improve program performance?

2.2 KEY FACTS ABOUT ELECTRIC VEHICLES IN SDG&E

Electric vehicles have the potential to transform the electric grid fundamentally. As the residential electric vehicle market grows, it will impact all aspects of the electric grid. Therefore, in addition to the load impacts achieved by the electric vehicle programs, it is also essential to understand the population and distribution of electric vehicles in SDG&E's service territory.

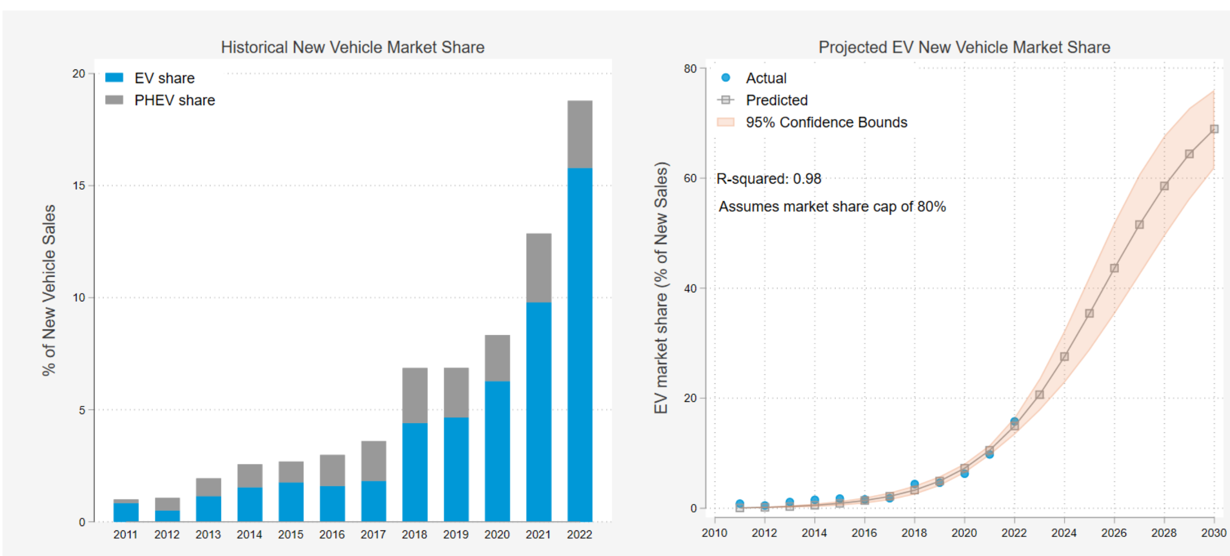
As of December 2021, over 2.8M vehicles were registered with the California DMV in SDG&E's service territory, which includes all of San Diego County and portions of South Orange County. In total, over 57,000 electric vehicles and 29,000 plug-in hybrid electric vehicles (PHEV) were registered in SDG&E territory. While the share of electric vehicles is small, the market share of electric vehicles is growing exponentially, as shown in Figure 1. In specific, electrified vehicles have grown as a share of new vehicles (100% battery electric or plug-in hybrid electric). Focusing on San Diego County, 18.8% of new vehicle sold were either full electric vehicles or plug-in hybrid vehicles. The historical market share penetration data has matured enough that vehicle share adoption can be estimated using historical data, as shown in Figure 2.

Figure 1: Electric Vehicle Population in SDG&E Territory (2022)



Source: California Energy Commission (2023). New ZEV Sales in California. Data last updated December 31, 2021. Retrieved February 17, 2023, from https://www.energy.ca.gov/zevstats

Figure 2: Electric Vehicle Market Share of New Vehicle Sales



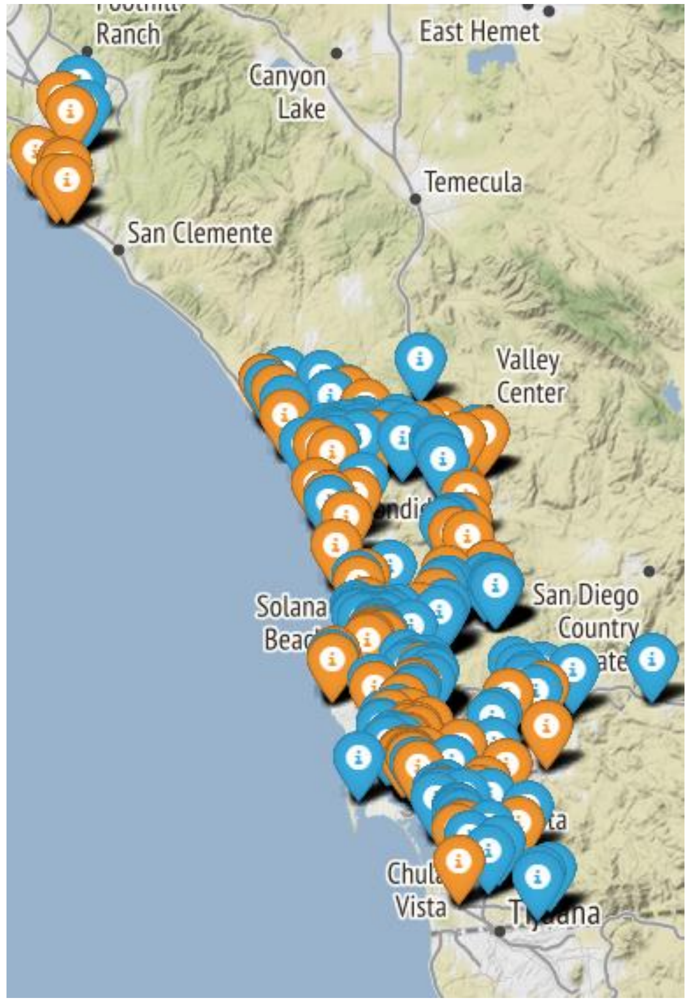
Data source: California Energy Commission (2022). New ZEV Sales in California. Retrieved February 17, 2023, from https://www.energy.ca.gov/zevstats Graphs and market share projection produced by DSA.

In preparation for growth in electric vehicles, SDG&E deployed an infrastructure program with a focus on encouraging EV adoption by reducing barriers such as the expense and difficulty of installing charging equipment at multi-family dwellings (MUDs) and workplaces. SDG&E deployed 2,611 charging ports at 211 locations. A total of 34% of the chargers are located in multi-family dwellings, and 34% of sites are located in disadvantaged communities.

Figure 3: SDG&E Vehicle Grid Integration Electric Vehicle Chargers

KEY FACTS

- There are 211 sites, 2,611 ports, and 2,562 actively enrolled drivers.
- 161 Sites are registered for rate-to-driver billing, representing 76% of the total.
- 74% of all stations are installed at rate-to-driver sites.
- 96% of the 2,562 actively enrolled drivers are enrolled at rate-to-driver sites.



2.3 2022 GRID CONDITIONS

SDG&E delivers electricity to 3.7 million people in San Diego and southern Orange counties. It has 1.4 million residential and business accounts, a service that area spans 4,100 square miles, and a peak demand of over 4,000 MW. SDG&E is responsible for ensuring that electricity supply remains reliable by projecting future demand and reinforcing the transmission and distribution network so that sufficient capacity is available to meet local needs as they grow over time. SDG&E is part of the California Independent System Operator (CAISO) electricity market.

The electric grid is unique in that supply and demand must be balanced nearly instantaneously because an imbalance can lead to cascading outages and compromise the reliability of the entire grid. The California System Operator has the critical role of balancing supply and demand and thus ensuring grid reliability. Historically, the electric grid infrastructure has been sized to meet the aggregate demand of end-users when it is forecasted to be at its highest—peak demand. With the introduction of large amounts of solar and wind power, the focus of planning has shifted to ensure enough flexible resources are in place to meet the demand that cannot be met by solar and wind alone – known as net loads.

Meeting peak demand requires procuring enough supply capacity to meet peak demand and maintaining sufficient operating reserves to absorb system shocks such as unscheduled generator outages, transmission outages, and large unforeseen swings in demand or supply. However, peak demand conditions occur infrequently – one or two times every ten years or so – and thus, planning for a small number of extreme conditions drives a significant share of infrastructure costs. An alternative to building additional peaking power plants is to reduce coincident demand by injecting power within the distribution grid (e.g., battery storage) or by reducing or shifting demand. The EVTOU and VGI prices encourage customers to shift usage to lower-priced hours when the electric grid is not peaking.

Figure 4 shows the hourly load pattern for the ten highest load days for SDG&E, CAISO, and CAISO net loads. Over the study period (Oct 2021-Sep 2022), peak demands were higher than in historical years: SDG&E peaked at 4,162 MW, CAISO peaked at 43,615 MW, and CAISO net loads peaked at 41,776 MW. Figure 5 shows the concentration of demand visualized with a normalized load duration curve. A load duration curve is a way to visualize "peakiness" or utilization of a system. It simply ranks each hour of the year based on demand from highest to lowest. If targeted precisely, shaving loads on the top 1% of hours at SDG&E would lead to an 18% reduction (~740 MW) in generation capacity needs at SDG&E. Likewise, a small number of hours drives peak planning and infrastructure costs for the California system. Shaving CAISO net loads on the top 1% of hours would lead to a 23% reduction (~9,500 MW) in need for generation capacity. Figure 6 shows the hourly electricity market prices for the SDG&E area from May to September 2021. The high price periods coincided with times when CAISO net loads were highest.

Figure 4: SDG&E and CAISO Top Ten Peak Load Days (Oct 2020-Sep 2021)

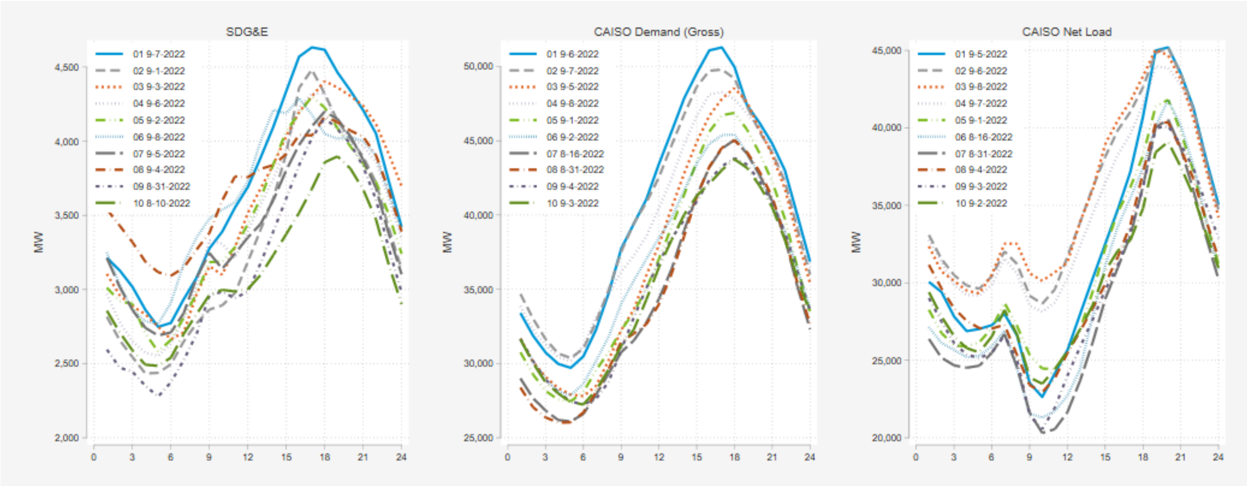


Figure 5: Normalized Load Duration Curves (Oct 2020-Sep 2021)

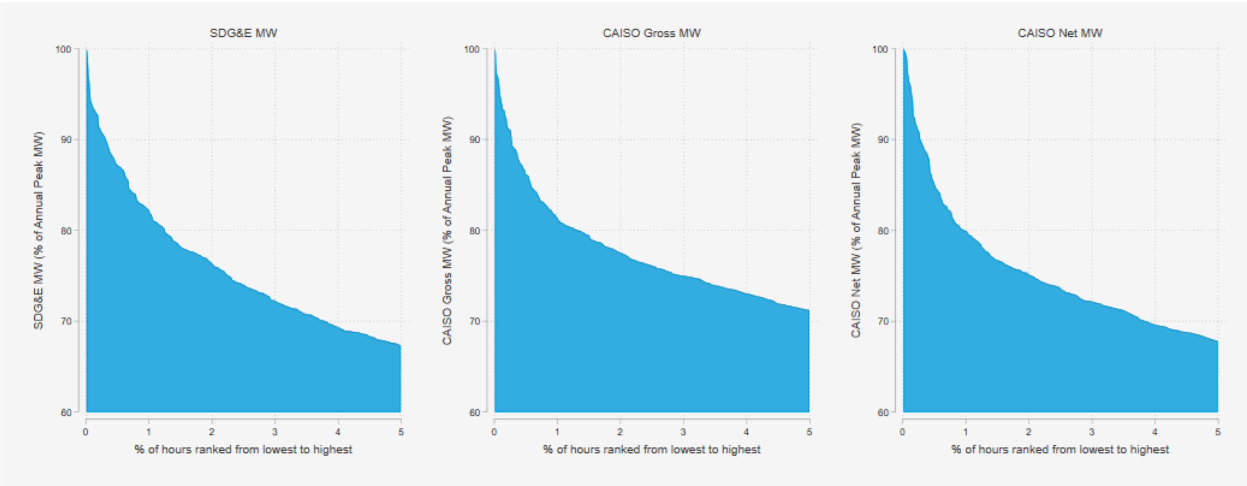


Figure 6: SDG&E Hourly Electricity Market Prices

3 METHODOLOGY

The primary challenge of impact evaluation is the need to accurately detect changes in energy consumption while systematically eliminating plausible alternative explanations for those changes, including random chance. Did the dispatch of demand response resources cause a decrease in hourly demand? Or can the differences be explained by other factors? To estimate demand reductions, it is necessary to estimate what demand patterns would have been in the absence of dispatch – this is called the counterfactual or reference load. At a fundamental level, the ability to measure demand reductions accurately depends on four key components:

- The effect or signal size – The effect size is most easily understood as the percent change. It is easier to detect large changes than it is to detect small ones. For most DR programs, the percentage change in demand is relatively large.
- Inherent data volatility or background noise – The more volatile the load, the more difficult it is to detect small changes. Energy use patterns of homes with air conditioners tend to be more predictable than industrial load patterns.
- The ability to filter out noise or control for volatility – At a fundamental level, statistical models, baseline techniques, and control groups – no matter how simple or complex – are tools to filter out noise (or explain variation) and allow the effect or impact to be more easily detected.
- Sample/population size – For most of the programs in question, sample sizes are not relevant because we plan to analyze data for the full population of participants either using AMI data or thermostat runtime. Sample size considerations aside, it is easier to precisely estimate average impacts for a large population than for a small population because individual customer behavior patterns smooth out and offset across large populations.

A key factor for many, but not all, demand response resources is the ability to dispatch the resource. The primary intervention – a dispatch or price signal – is introduced on some days and not on others, making it possible to observe energy use patterns with and without demand reductions. This, in turn, enables us to assess whether the outcome – electricity use – rises or falls with the presence or absence of demand response dispatch instructions. The exception is TOU rates, which are discussed in more detail below.

3.1 EV TOU RATE METHODOLOGY

Once a customer is on a TOU rate, the TOU rate is in place every day, and it is no longer possible to observe their behavior absent TOU rates. Thus, estimating TOU effects requires a control group and, ideally, a year of pre-treatment and post-treatment data for both the TOU and control groups. The pre-treatment data is useful for assessing if energy consumption changed and allows the use of more powerful statistical techniques such as difference-in-difference models. When neither group is on TOU rates, the energy use patterns should be nearly identical. If the TOU rates lead to changes in energy use, we should observe a change in consumption for customers who went on the TOU rate but no similar change for the control group. In addition, the timing of the change should coincide with the adoption of TOU rates.

Ex-Post Evaluation Approach

Key issues that influenced the ex-post evaluation approach are:

- Identifying an appropriate control pool. The primary challenge in evaluating electric vehicle programs is finding appropriate control customers. The appropriate control pool is customers who have electric vehicles but have not signed onto the EV TOU rate. However, SDG&E only has conclusive data about EV ownership for homes that sign onto TOU rates for electric vehicles. DSA used AMI data to develop electric vehicle propensity estimates and identify sites with electric vehicles that were not on TOU rates for electric vehicles. In developing the propensity models, we intentionally avoided variables that focus on hourly load patterns and overall consumption since both are influenced by the TOU rates for electric vehicles. Instead, the markers to identify electric vehicles were focused on max demand values on temperate days when air conditioning loads were not present.
- Electric vehicle adoption often coincides with enrollment in the TOU rate and solar or battery storage adoption. When multiple changes occur at once, it is more difficult to isolate the effect of the TOU rates. It is necessary to eliminate from the analysis both participants and control candidates that purchased their electric vehicle or had solar or battery installation near the time they enrolled on the EVTOU rate. SDG&E provided access to their interconnection data, allowing us to remove sites with changes in solar or battery status over the analysis period. For electric vehicles, DSA developed and applied an algorithm to identify the timing of adoption of the electric vehicle.
- Rolling enrollments versus first-year patterns. Customers adopt and sign on to electric vehicle rates at different points in time. The pattern can create imbalanced time series and lead to spurious effects. Thus, the primary analysis is based on sites with a full year before and a full year after customers transitioned to the electric vehicle TOU rates.

The above factors were taken into consideration in selecting our evaluation approach, which is summarized in Table 3.

Table 3: EV TOU Ex-Post Evaluation Approach Summary

	Methodology Component	Description
1.	**Population or sample analyzed**	The evaluation focused only on incremental sites that reached their full first year savings between October 1, 2021 and September 2022. It excluded sites who had a change in electric vehicle, solar, or battery status that coincided with the study period. The full population of incremental participants with a full year of data before and a full year of data after electric vehicle TOU rate adoption. The evaluation included approximately 20% of the incremental enrollments as customers often enroll on TOU rates for electric vehicles shortly after getting their electric vehicle.
2.	**Data included in the analysis**	The analysis included a full year of pre and a full year of post TOU data. The same data was included for participants and matched control. In all cases, we ensured that both the participant and control had pre and post TOU data for the same day of year.
3.	**Use of control groups**	We relied on a control group of customers with electric vehicles but that were not on SDG&E's TOU rates for electric vehicles. The process to find this control group

Methodology Component	Description
	involves two steps. First, we build electric vehicle propensity using AMI data to identify unique load patterns that indicate the presence of electric vehicles (but avoiding variables about load shape and overall consumption). As part of the analysis we also identified the approximate date the electric vehicle(s) arrived at the household. Once control candidates with electric vehicles had been identified, we matched customers using pre-treatment hourly AMI data. The matching on pre-treatment loads used Euclidian distance matching and matches were selected only from customers with similar electric vehicle scores. Participants were paired to the matched control site and the control site was assigned the same "treatment date" as the participant.
4. **Evaluation Method**	Simple difference-in-differences was used to isolate the load impact. The process involved the following steps: 1. Aggregate (or average) the data to the relevant time unit of analysis. This was done for both participants and control and for the year before and after the treatment. 2. The difference between the before and after period was calculated for the treatment group 3. The difference between the before and after time period was calculated for the control group. 4. The difference observed in the control group was netted out of the participant difference to produce the difference-in-differences.
5. **Model selection**	The approach relies more heavily on selecting a comparable matched control group than the model specification. We conducted a tournament to identify the model that performed best (least percent bias and relative RMSE) at identifying the control pool.
6. **Segmentation of impact results**	The results were segmented by: ▪ Rate ▪ Region in SDG&E territory (based on 3-digit zip code) ▪ Solar status ▪ Low income

EX-ANTE EVALUATION APPROACH

A key objective of the DR evaluations is to quantify the relationship between demand reductions, temperature, hour-of-the-day, and dispatch strategy. The purpose of doing so is to establish the demand reduction capability under 1-in-2 and 1-in-10 weather conditions for planning purposes and, increasingly, for operations. When possible, we rely on the historical event performance to forecast ex-ante impacts for future years for different operating conditions.

At a fundamental level, the process of estimating ex-ante impacts is simple:

1. Decide on an adequate segmentation to reflect how the customer mix evolves over time.
2. Estimate the relationship between reference loads and weather

3. Use the models to predict reference loads for different weather conditions (e.g., 1-in-2 and 1-in-10 weather year conditions)
4. Estimate the relationship between weather and impacts
5. Predict load impacts for different weather conditions
6. Combine the reference loads (#4) and impacts (#6) to produce per-customer impacts
7. Multiply per-customer impacts by the enrollment forecast

The process can be used to develop ex-ante estimates of demand reduction as a function of different temperatures and day types. It can be used to develop estimates for 1-in-2 and 1-in-10 weather year planning conditions, and it can be used to develop time-temperature matrices useful for estimating reduction capability for operations or a wider range of planning conditions.

Table 4: EV TOU Ex-Ante Evaluation Approach Summary

Methodology Component	Demand Side Analytics Approach
1. Years of historical data	Data from the year prior to the adoption of EVTOU rates for each customers was used to develop reference loads. The load reductions for a full year of EVTOU participation were used to model ex-ante load impacts
2. Process for producing ex-ante impacts	The key steps were: ▪ Segment customers by rate type (EVTOU5 and EVTOU2) and solar status ▪ Estimate the relationship between reference loads and weather on a per household basis. ▪ Use the models to predict reference loads for 1-in-2 and 1-in-10 weather year conditions. ▪ Estimate the relationship between EVTOU load impacts and weather ▪ Predict the reductions for 1-in-2 and 1-in-10 weather year conditions ▪ Combine per customer reference loads and load impacts with an incremental forecast of enrollment on EV TOU rated developed by SDG&E.
3. Accounting for changes in the participant mix	The ex-ante load impacts account for changes in the participant mix across the two main rate types – EVTOU2 and EVTOU5 – and rooftop solar status.
4. Producing busbar level impacts	Granular results for distribution planning have been required for the last few years. A key consideration in the approach is that there is more data about customer loads than there is data on the percent reductions delivered during events. To develop ex-ante impacts at the busbar level, we use the load impacts by segment and the current mix of customers at the busbar level to estimate the granular impacts.

3.2 VEHICLE GRID INTEGRATION METHODOLOGY

The unique VGI rate design and billing makes it challenging to evaluate compared to traditional event based programs. Customers enroll on this rate specifically for access to SDG&E's charging infrastructure at workplaces and multi-family dwellings. The only consumption is through EVs plugging into the charging infrastructure.

EVALUATION APPROACH

The key challenges that affect the evaluation approach are:

- Lack of a control group. Most Level 2 workplace and multi-family chargers are enrolled in the SDG&E program, making it difficult to develop a control group that did not face the dynamic rates. Thus, the evaluation relies on estimating the relationship between customer charging patterns and the variation in hourly prices.
- Lack of a clear pricing counterfactual. Unlike residential and non-residential rates, the rate customers would face if they were not enrolled on VGI is not known.
- Inability to observe shifting between home and workplace or public charging. The only data metered is the usage at SDG&E charging stations. However, customers have the ability to charge at home, at workplaces, at public charging sites, and at DC fast charging stations. Thus, there is the possibility of shifting between the charging options based on the relative prices.
- Session-data only includes periods when vehicles are charging. If analyzed on its own, sessions data leaves out critical information about hours when charging ports are not plugged into an electric vehicle. To create a full picture without critical gaps we converted the session data to hourly interval data and filled in gaps to reflect that zero kW is drawn when the vehicle is not in a charging session.

Table 5: Vehicle Grid Integration Ex-Post Evaluation Approach Summary

Methodology Component	Demand Side Analytics Approach
1. **Population or sample analyzed**	Charging data from all VGI charging sessions from October 1, 2021 through September 30, 2022 were provided for the evaluation. We analyzed charging sessions throughout this period.
2. **Data included in the analysis**	For the VGI evaluation, we utilized: ▪ Charging session level kWh consumption data ▪ Driver Enrollment Data ▪ Site and Station characteristics ▪ Charging $/kWh prices by day, hour, and station ▪ Historical weather patterns from Weather station records
3. **Evaluation Method**	Panel regression by charging port with multiple fixed effects. We implemented a price response model and "event response" model, which treated periods with generation or distribution capacity adders as events. The price response model estimated price elasticities (% change in load associated with a 1% change in prices). The Event based model flagged hours with circuit or system Critical Peak Pricing adders as events. The coefficients of these models demonstrate the magnitude of customer response to measured changes in pricing as well as event hours.

4.	**Model selection**	To estimate customer response we ran linear regressions with multiple fixed effects and multi-way clustering. The regressions controlled for the nozzle ID (fixed effect), date (time effect), day of week, and hour.
5.	**Segmentation of impact results**	The results will be segmented by: ▪ Site type: Workplace vs. Multi-Unit Dwellings ▪ Rate to Host vs. Rate to Driver

4 ELECTRIC VEHICLE TOU EX-POST RESULTS

This section focuses on the magnitude of demand reductions delivered by incremental EV TOU participants for the time frame from October 1, 2021 to September 30, 2022. SDG&E has two primary whole premise rates for electric vehicles, EVTOU2 and EVTOU5. The rates encourage customers to shift their use from higher priced periods to lower cost periods, but do not directly control the charging behavior of customers or vehicles.

Figure 7: Total Enrollments by EV TOU Rate type

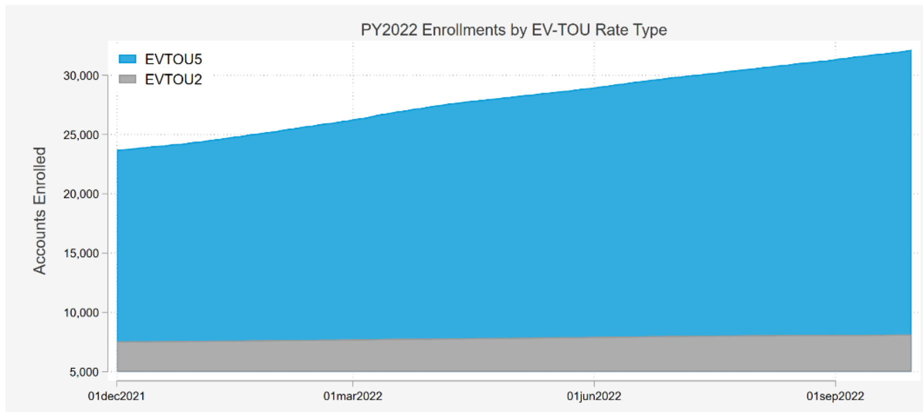
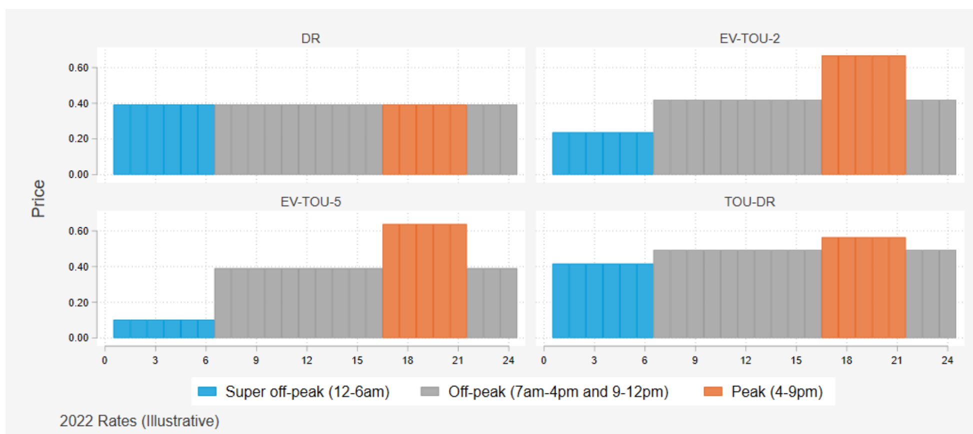


Figure 8: Residential Rates Sumer 2021 Prices



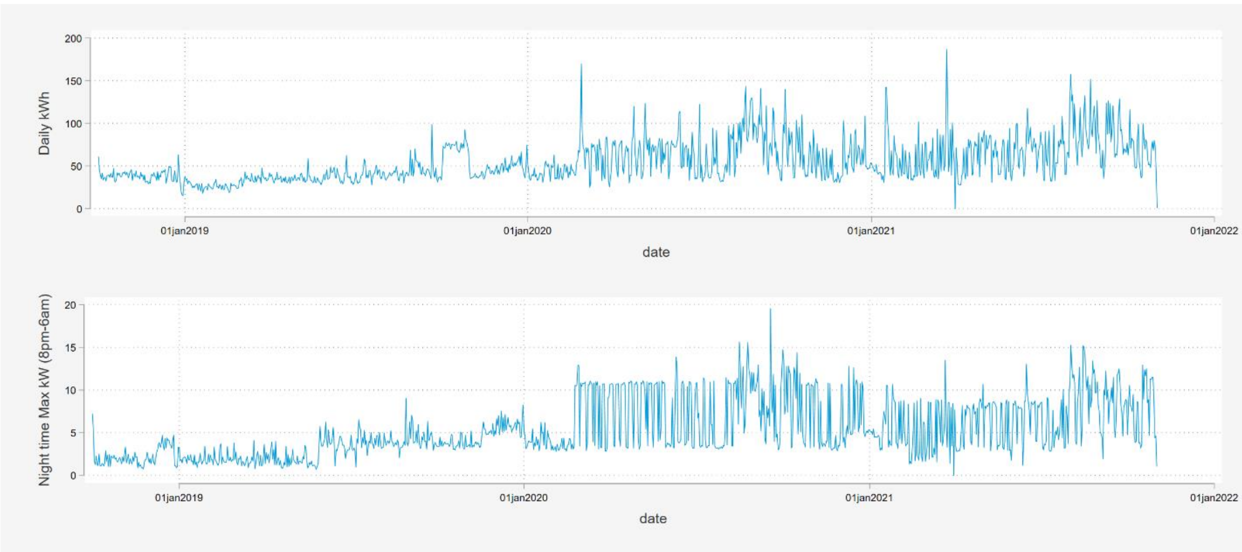
Overall, SDG&E has signed over 30,000 homes onto electric vehicle TOU rates. For context, SDG&E has roughly 57,000 full battery electric vehicles and 29,000 plug-in hybrid vehicles in its territory. Since mid-2018 most electric vehicles have signed onto the EVTOU5 rate, which has a higher fixed charge and substantially lower overnight rates. When the EVTOU5 rate was first introduced, many EVTOU2 customers switched onto it. However, by PY2022, the rates were largely stable and switching between electric vehicle rates was negligible.

Participation in the rates is voluntary and customers selected the TOU rates for electric vehicles over the default rate flat domestic rate (DR) and the default TOU rate (TOU-DR) that applies to roughly 60% of SDG&E customers. Notably, the EVTOU2 and EVTOU5 rates have higher peak prices (4-9 PM) and lower super-off-peak peak prices (12-6AM). Thus, the rates encourage customers to shift usage more than SDG&E's default time of use rate (TOU-DR).

4.1 CHARGING PATTERNS BEFORE AND AFTER TOU RATES FOR ELECTRIC VEHICLES

The early adopters of electric vehicles differ from the typical SDG&E customers. They are more likely to own solar and battery storage and are typically wealthier. When an electric vehicle is introduced, it fundamentally changes usage and max demand at a home. Figure 9 illustrates how the introduction of an electric vehicle leads to an increase in daily use, an increase in daily max demand, and increased volatility in energy use. The change is most obvious for customers with an electric vehicle Level 2 charger and for the maximum daily demand between hours from 8 PM – 6 PM.

Figure 9: Example of How the Introduction of Electric Vehicle Change Household Energy Use



To isolate the effects of TOU we used the AMI data to identify customers with a similar electric vehicle footprint that were not on TOU rates for electric vehicles to serve as controls. In addition, we removed any participants and candidate controls where the change in electric vehicle ownership appeared to coincide with the adoption of TOU rates for electric vehicles. The participants were then matched to customers with similar electric vehicle footprints and a similar whole home load pattern during the time frame when neither participants nor the control candidates where on TOU rates.

Figure 10 show the hourly load patterns for the EV TOU customers and the corresponding controls both before and after the participants enrolled on the rate. The plots reflect the raw data without any modeling. When neither group was on TOU rates, the electricity patterns mirrored each other, with small differences. Once participants go on TOU rates, the electric use patterns diverge. Customers on TOU rates for electric vehicles increased usage between 12-6pm when prices were lowest, and decreased usage during the higher prices hours. Although the electric vehicle rates differ for 4-9 pm, participants reduced usage during both off-peak (6AM-4PM and 10PM-12PM) and peak hours (4-9 pm). Table 6 shows the data underlying Figure 10, and shows the difference-in-difference calculation, which nets out pre-existing observed differences.

Figure 10: Hourly Load Patterns Before and After EVTOU Rates (May-October)

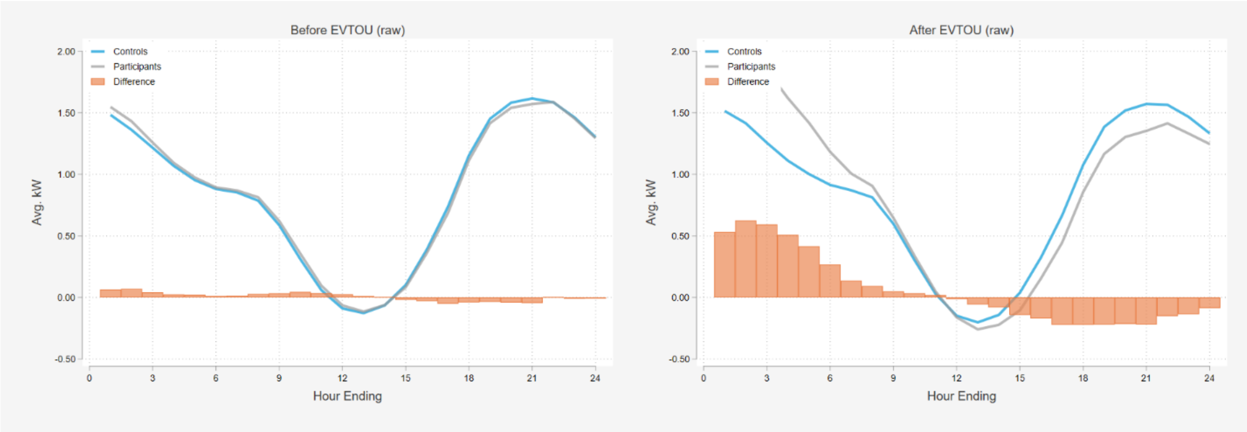


Table 6: First Year Hourly Differences-in-Differences

Hour Start	Treatment (n = 791) Before	After	Diff	Control (n=791) Before	After	Diff	Difference-in-Differences Impact	Std. Error	t-stat
0:00	1.55	2.01	0.46	1.47	1.48	0.01	0.45	0.046	9.93
1:00	1.44	2.02	0.58	1.35	1.38	0.03	0.55	0.045	12.12
2:00	1.26	1.82	0.56	1.21	1.23	0.02	0.54	0.040	13.63
3:00	1.10	1.59	0.49	1.06	1.09	0.02	0.47	0.034	13.67
4:00	0.98	1.39	0.41	0.95	0.99	0.04	0.38	0.031	11.99
5:00	0.90	1.17	0.27	0.88	0.91	0.02	0.25	0.024	10.42
6:00	0.88	1.01	0.13	0.86	0.88	0.01	0.11	0.018	6.21
7:00	0.83	0.92	0.09	0.80	0.83	0.03	0.06	0.018	3.32
8:00	0.63	0.66	0.03	0.59	0.61	0.02	0.01	0.021	0.51
9:00	0.36	0.35	-0.01	0.32	0.32	0.00	-0.02	0.025	-0.69
10:00	0.10	0.05	-0.05	0.06	0.04	-0.02	-0.02	0.028	-0.86
11:00	-0.06	-0.16	-0.10	-0.08	-0.14	-0.05	-0.04	0.029	-1.55
12:00	-0.11	-0.25	-0.14	-0.12	-0.20	-0.07	-0.07	0.028	-2.53
13:00	-0.05	-0.21	-0.16	-0.06	-0.13	-0.07	-0.08	0.028	-3.07
14:00	0.09	-0.09	-0.19	0.12	0.05	-0.07	-0.12	0.026	-4.61
15:00	0.38	0.17	-0.21	0.41	0.34	-0.07	-0.14	0.023	-5.86
16:00	0.71	0.46	-0.24	0.76	0.68	-0.08	-0.17	0.023	-7.22
17:00	1.13	0.87	-0.26	1.17	1.09	-0.08	-0.18	0.022	-7.94
18:00	1.41	1.16	-0.25	1.45	1.39	-0.06	-0.18	0.023	-8.13
19:00	1.52	1.29	-0.23	1.57	1.51	-0.06	-0.18	0.024	-7.55
20:00	1.55	1.33	-0.22	1.59	1.56	-0.04	-0.18	0.024	-7.49
21:00	1.56	1.38	-0.18	1.56	1.54	-0.02	-0.16	0.028	-5.62
22:00	1.43	1.30	-0.13	1.44	1.44	0.00	-0.13	0.030	-4.42
23:00	1.28	1.21	-0.07	1.28	1.30	0.02	-0.09	0.031	-2.84

Figure 11 shows average demand from 4-9 pm for each day for the full year before and after the introduction of the EVTOU rates by day-of-year. The energy use patterns are similar for the treatment and control groups before the official adoption of the TOU rates for electric vehicles, but there are small differences. Those pre-existing differences are removed or netted out in the differences-in-differences technique.

Figure 11: Peak Period (4-9 PM) Daily Differences Before and After TOU Rates for Electric Vehicles

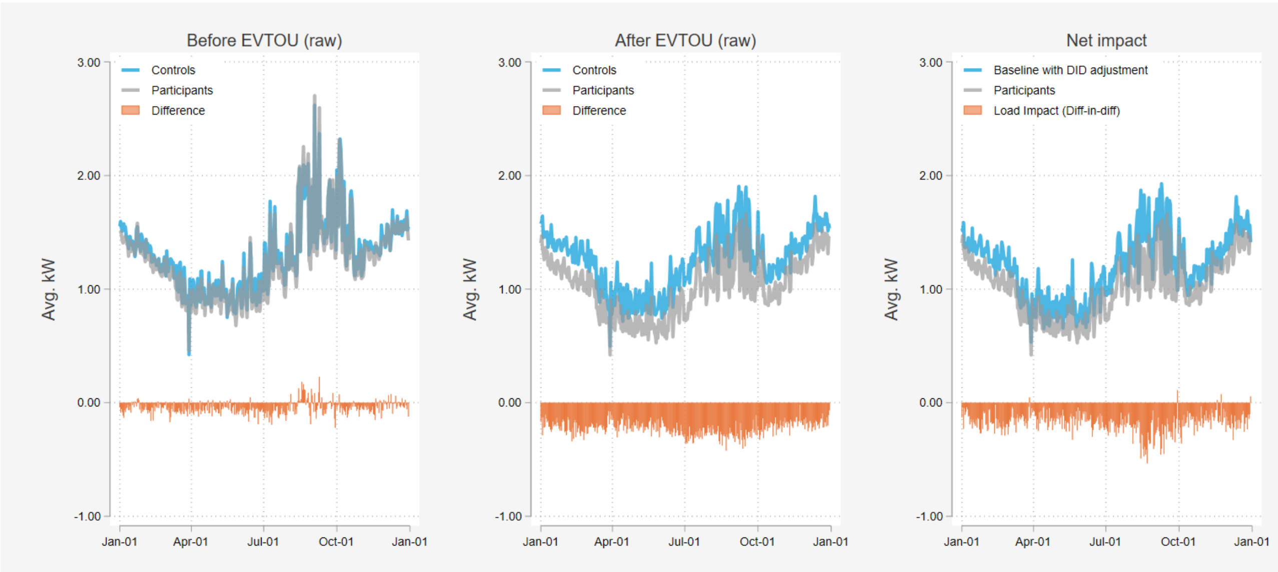
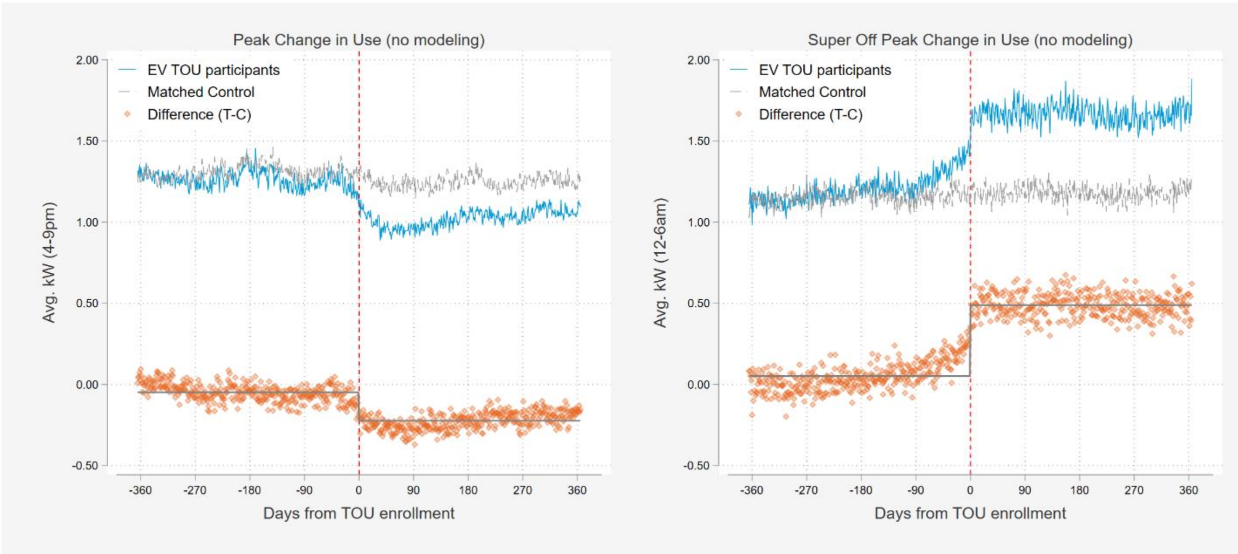


Figure 12 also shows the differences by day of year, but it compares the 365 days immediately before and after enrollment based on the days from enrollment. Thus, it normalizes the time dimensions allowing for direct comparison of sites that enrolled on different dates. As before, the energy use patterns are similar for the treatment and control groups before the official adoption of the TOU rates for electric vehicles, but there are small differences. The change in energy usage for participants roughly coincides with the adoption of the rates and the change in energy usage matches the expected price response. Participants decrease energy use when prices are higher and reduce demand when prices are lower. The shift in behavior does not coincide perfectly because billing periods differ by customer and customers may consider changes over multiple days and weeks in advance of the transition to electric vehicle rates.

Figure 12: Treatment and Control Group Differences by Days from Treatment



4.2 LOAD IMPACTS ON HIGHEST SYSTEM LOAD DAYS

Although EV TOU customers have a daily incentive to shift load away from hours when prices are highest, peak hours, and charge when prices are lowest, it is critical to understand how the rates change load pattern when demand is highest. As noted earlier, many grid infrastructure components are sized to meet the aggregate peak demand levels that occur infrequently. When customers reduce demand coincident with the peaks that drive infrastructure needs – either by injecting power within the distribution grid (e.g., behind-the- meter generation) or by reducing demand – they often help avoid the costs associated with infrastructure expansion. Notably, different parts of the grid can peak at different times. As Figure 4 showed, the SDG&E system peaks on different days than CAISO demand, which, in turn, differs from the days when CAISO net loads are highest.

Figure 13 shows the average hourly demand reduction from EV TOU participants in the 10 days when demand was highest for CAISO, CAISO net loads, and SDG&E. The change in peak and super-offpeak demand is similar for all three.

Table 5 provides additional detail about the load impacts for the top 5, 10, and 20 highest load days for CAISO, CAISO net loads, and SDG&E. The reduction were larger in magnitude on the top 5 highest system load days than on the top 10 and top 20 highest system load days. Simply put, customers on TOU rates for electric vehicles delivered larger demand reductions when resources were needed most.

Figure 13: Hourly Load Impacts on Top Highest Load Days by System

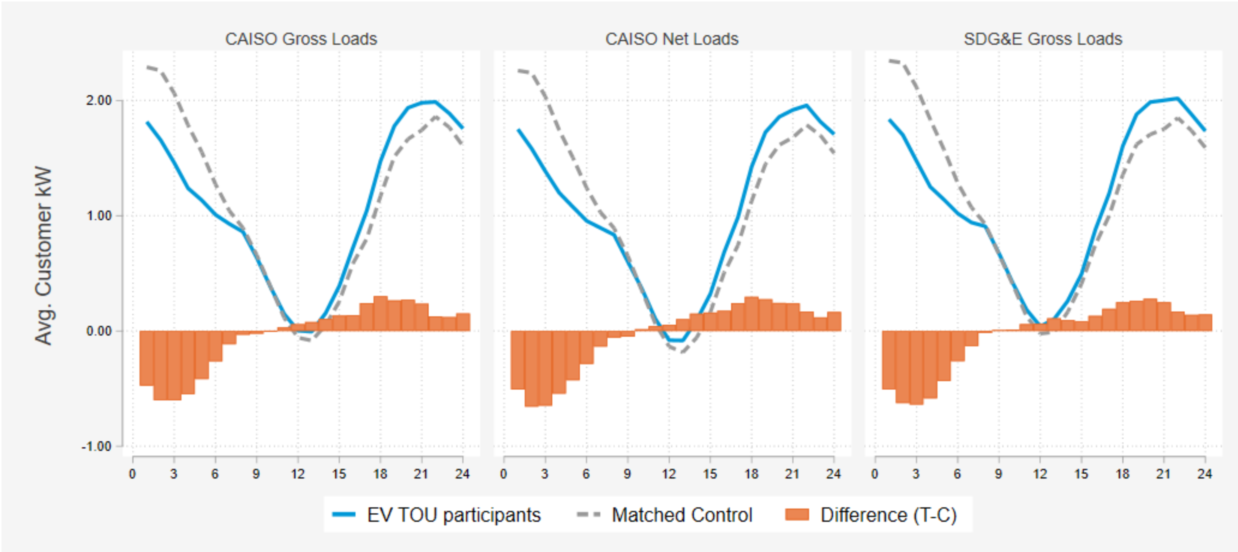


Table 7: Ex-post Load Impacts on Highest System Load Days (4-9 pm)

System	Month	Sample[1]	New Accts	Total Accts	Daily Avg. Temp[2]	Avg. Customer (kW) Reference Load	Load Reduction	% Reduction	New Load Impact (MW)	Total Load Impact (MW)
CAISO Gross Loads	Top 05 load day(s)	791	5,533	31,351	75.6	1.69	0.28	16.5%	1.55	8.76
	Top 10 load day(s)	791	5,533	31,351	75.8	1.64	0.26	16.0%	1.46	8.27
	Top 20 load day(s)	791	5,533	31,351	75.1	1.55	0.25	15.9%	1.36	7.72
CAISO Net Loads	Top 05 load day(s)	791	5,533	31,351	75.8	1.70	0.26	15.1%	1.42	8.03
	Top 10 load day(s)	791	5,533	31,351	74.9	1.58	0.26	16.4%	1.44	8.14
	Top 20 load day(s)	791	5,533	31,351	74.4	1.55	0.27	17.3%	1.48	8.39
SDG&E Gross Loads	Top 05 load day(s)	791	5,533	31,351	77.7	1.81	0.26	14.1%	1.41	8.02
	Top 10 load day(s)	791	5,533	31,351	75.1	1.73	0.25	14.2%	1.36	7.73
	Top 20 load day(s)	791	5,533	31,351	75.4	1.69	0.25	15.1%	1.41	7.97

[1] Estimating sample is lower than populations because it excludes sites that whose transition to EV TOU coincided with the arrival of the electric vehicle or with solar or battery installation.
[2] Participant weighted average temperature. SDG&E maps all customers to eight distinct weather stations.

4.3 LOAD IMPACTS FOR MONTHLY PEAK DAY

Table 8 summaries the hourly demand reductions for the peak days in each month. In general, estimating TOU impacts for a single hour is more difficult and noisier than estimating impacts for the average day of each month. Thus, we used to top 3 SDG&E load day for each month and also recommend a degree of caution in reviewing the monthly peak day impacts.

Table 8: Ex-post Monthly Peak Day (SDG&E) Hourly Demand Reductions per Site

Hour Ending	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sep	Oct	Nov	Dec
1	-0.66	-0.62	-0.35	-0.49	-0.50	-0.35	-0.53	-0.40	-0.52	-0.45	-0.53	-0.51
2	-0.65	-0.65	-0.58	-0.55	-0.67	-0.50	-0.55	-0.49	-0.66	-0.47	-0.62	-0.56
3	-0.59	-0.58	-0.66	-0.59	-0.69	-0.51	-0.57	-0.52	-0.64	-0.42	-0.66	-0.55
4	-0.46	-0.54	-0.64	-0.51	-0.59	-0.45	-0.53	-0.48	-0.54	-0.36	-0.49	-0.50
5	-0.38	-0.43	-0.48	-0.44	-0.41	-0.38	-0.39	-0.36	-0.37	-0.28	-0.39	-0.41
6	-0.22	-0.25	-0.33	-0.28	-0.31	-0.29	-0.22	-0.21	-0.22	-0.23	-0.27	-0.29
7	-0.15	-0.14	-0.13	-0.14	-0.14	-0.16	-0.14	-0.08	-0.17	-0.08	-0.10	-0.15
8	-0.16	-0.01	-0.07	-0.16	-0.07	-0.09	-0.05	0.02	-0.07	-0.03	-0.06	-0.03
9	-0.15	0.14	-0.01	-0.05	0.01	-0.01	-0.01	0.05	-0.01	-0.01	0.01	0.05
10	-0.05	0.12	0.03	0.06	0.02	0.07	-0.03	0.07	-0.01	-0.01	0.02	0.05
11	-0.03	0.09	0.04	0.03	0.04	0.05	-0.02	0.10	0.02	0.05	0.10	0.01
12	-0.03	0.12	0.01	0.01	0.09	0.12	0.00	0.09	0.01	0.13	0.09	0.05
13	0.05	0.04	0.09	0.05	0.12	0.20	0.00	0.16	0.10	0.07	0.05	0.11
14	0.08	0.11	0.17	0.05	0.14	0.18	0.01	0.11	0.04	0.08	0.06	0.05
15	-0.02	0.09	0.16	0.12	0.22	0.22	0.04	0.13	0.00	0.15	0.14	0.06
16	0.00	0.03	0.17	0.13	0.28	0.24	0.05	0.09	0.13	0.09	0.09	0.14
17	0.01	0.06	0.23	0.17	0.28	0.26	0.16	0.16	0.17	0.07	0.06	0.17
18	0.17	0.12	0.20	0.23	0.31	0.24	0.26	0.17	0.23	0.10	0.09	0.26
19	0.14	0.23	0.10	0.18	0.23	0.14	0.29	0.22	0.31	0.15	0.11	0.28
20	0.17	0.28	0.15	0.23	0.13	0.07	0.23	0.28	0.29	0.19	0.14	0.27
21	0.17	0.24	0.20	0.12	0.15	0.15	0.19	0.18	0.30	0.25	0.14	0.25
22	0.09	0.16	0.13	0.10	0.20	0.18	0.13	0.13	0.22	0.18	0.15	0.22
23	0.13	0.22	0.11	0.17	0.14	0.17	-0.02	0.12	0.18	0.18	0.14	0.20
24	0.05	0.19	0.04	0.05	0.15	0.09	0.04	0.16	0.17	0.26	0.13	0.07

Demand Reductions are positive (Blue)

Load increase are negative (Orange)

Error! Not a valid bookmark self-reference. **visualizes the hourly load impacts for the monthly peak day of each month. It shows the actual load for sites on EV TOU and the reference load or counterfactual. The orange bar reflect the change in demand, or load impacts. A positive value indicates an increase in energy use and a negative value indicates a decrease in demand. In general use increased during the 12-6 AM period when**

prices were lowest and decreased during the peak window of 4-9 PM. Table 8Figure 14: Ex-post Monthly Peak Day (SDG&E) Hourly Load Impacts

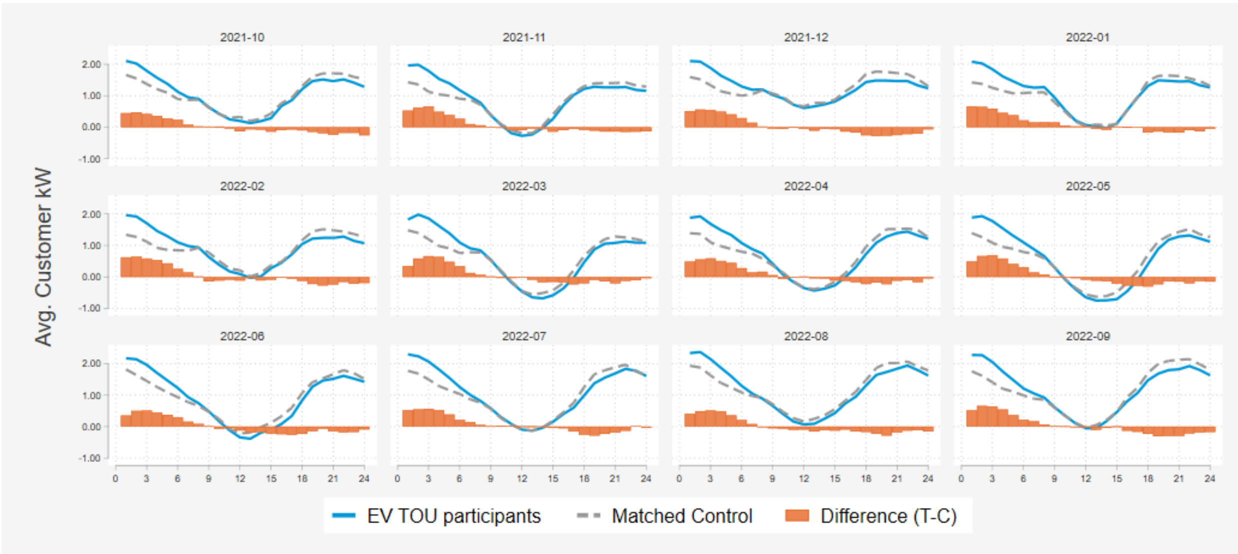


Table 9 summaries the hourly demand reductions for the average day in each month. Figure 15 visualizes the hourly load impacts for the monthly average day of each month. It shows the actual load for sites on electric vehicle rates and the reference load or counterfactual. The orange bar reflect the change in demand, or load impacts. A positive value indicates an increase in energy use and a negative value indicates a decrease in demand. In general use increased during the 12-6 AM period when prices were lowest and decreased during the peak window of 4-9 PM..

Figure 15: Ex-post Monthly Average Day Hourly Load Impacts

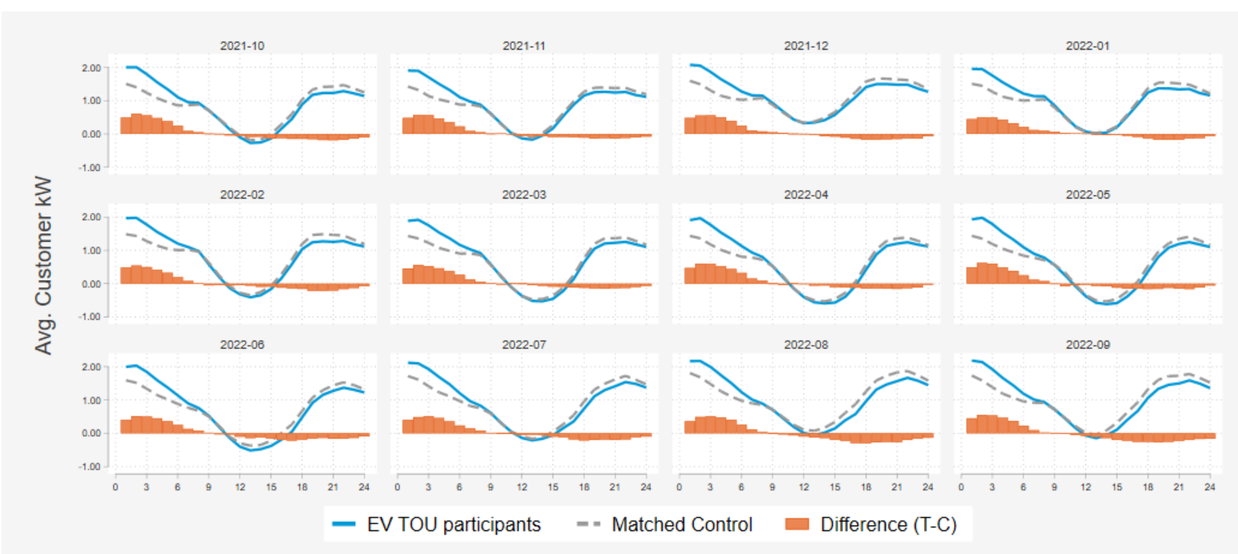


Table 9: Ex-post Monthly Average Day Hourly Demand Reductions per Site

Hour Ending	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sep	Oct	Nov	Dec
1	-0.45	-0.48	-0.46	-0.47	-0.50	-0.41	-0.40	-0.36	-0.45	-0.50	-0.48	-0.48
2	-0.50	-0.54	-0.56	-0.60	-0.63	-0.52	-0.49	-0.49	-0.56	-0.60	-0.57	-0.56
3	-0.49	-0.50	-0.53	-0.59	-0.60	-0.51	-0.51	-0.52	-0.54	-0.56	-0.56	-0.56
4	-0.43	-0.41	-0.46	-0.52	-0.48	-0.45	-0.46	-0.48	-0.47	-0.48	-0.47	-0.50
5	-0.33	-0.33	-0.38	-0.44	-0.38	-0.36	-0.36	-0.40	-0.37	-0.39	-0.36	-0.40
6	-0.21	-0.20	-0.26	-0.32	-0.25	-0.26	-0.23	-0.26	-0.23	-0.25	-0.23	-0.25
7	-0.12	-0.08	-0.12	-0.15	-0.12	-0.13	-0.14	-0.11	-0.10	-0.09	-0.09	-0.11
8	-0.09	-0.02	-0.06	-0.09	-0.07	-0.08	-0.08	-0.04	-0.02	-0.05	-0.05	-0.07
9	-0.06	0.05	-0.02	0.00	0.01	-0.02	-0.01	0.00	-0.01	-0.01	-0.01	-0.05
10	-0.03	0.04	0.03	0.04	0.08	0.03	0.00	0.03	0.02	0.01	-0.01	-0.03
11	-0.02	0.06	0.00	0.00	0.05	0.04	0.00	0.06	0.05	0.05	0.02	0.00
12	-0.01	0.05	0.00	0.02	0.03	0.10	0.05	0.10	0.08	0.05	0.05	0.01
13	0.02	0.06	0.04	0.06	0.07	0.14	0.05	0.13	0.11	0.09	0.06	0.03
14	0.04	0.10	0.07	0.06	0.08	0.13	0.05	0.14	0.14	0.08	0.07	0.07
15	0.03	0.09	0.09	0.11	0.12	0.16	0.10	0.19	0.20	0.14	0.10	0.08
16	0.05	0.12	0.10	0.12	0.15	0.20	0.12	0.22	0.22	0.13	0.09	0.11
17	0.09	0.14	0.12	0.12	0.16	0.22	0.19	0.30	0.26	0.15	0.10	0.15
18	0.13	0.16	0.13	0.15	0.17	0.19	0.22	0.30	0.26	0.15	0.11	0.17
19	0.17	0.22	0.15	0.15	0.16	0.16	0.20	0.27	0.27	0.16	0.13	0.17
20	0.17	0.21	0.16	0.15	0.13	0.14	0.19	0.26	0.26	0.19	0.13	0.16
21	0.18	0.21	0.14	0.16	0.16	0.16	0.20	0.26	0.23	0.19	0.13	0.16
22	0.13	0.16	0.13	0.14	0.16	0.16	0.19	0.20	0.19	0.18	0.12	0.14
23	0.13	0.13	0.10	0.12	0.12	0.14	0.12	0.16	0.17	0.14	0.11	0.13
24	0.06	0.07	0.07	0.03	0.05	0.09	0.10	0.14	0.17	0.11	0.08	0.07

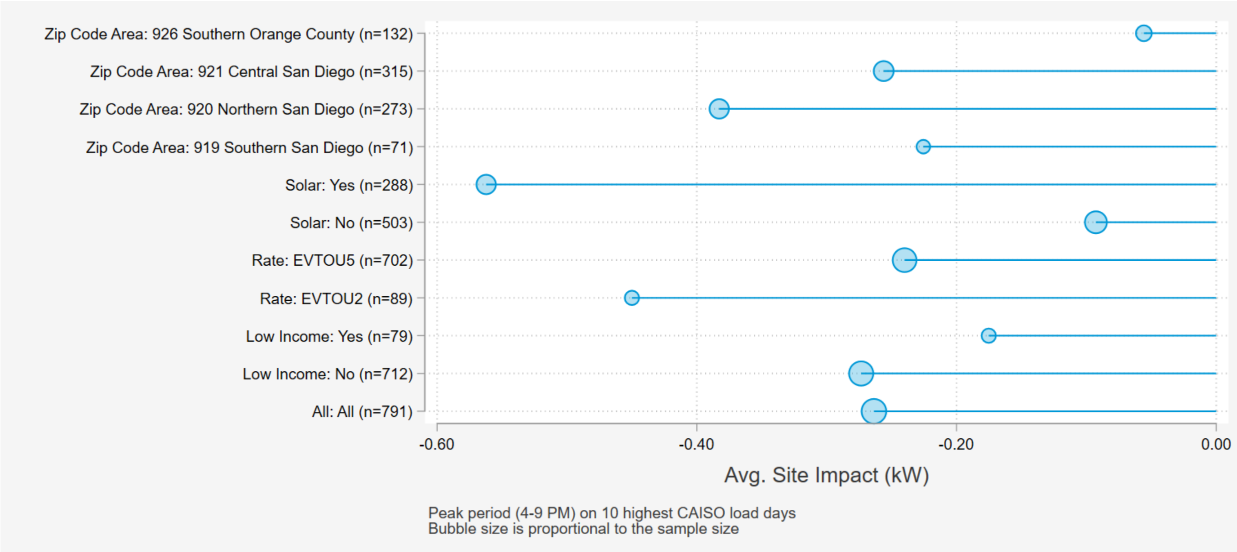
Demand Reductions are positive (Blue)

Load increases are negative (Orange)

4.4 LOAD IMPACTS BY CUSTOMER TYPE

Figure 16 shows the impacts of key customer segments for the peak period (4-9PM) on the ten highest CAISO system load days. The summary is descriptive, not causal, but informative nonetheless. We caution that results are noisier when the estimating sample size is smaller such as for the EVTOU2 rate.

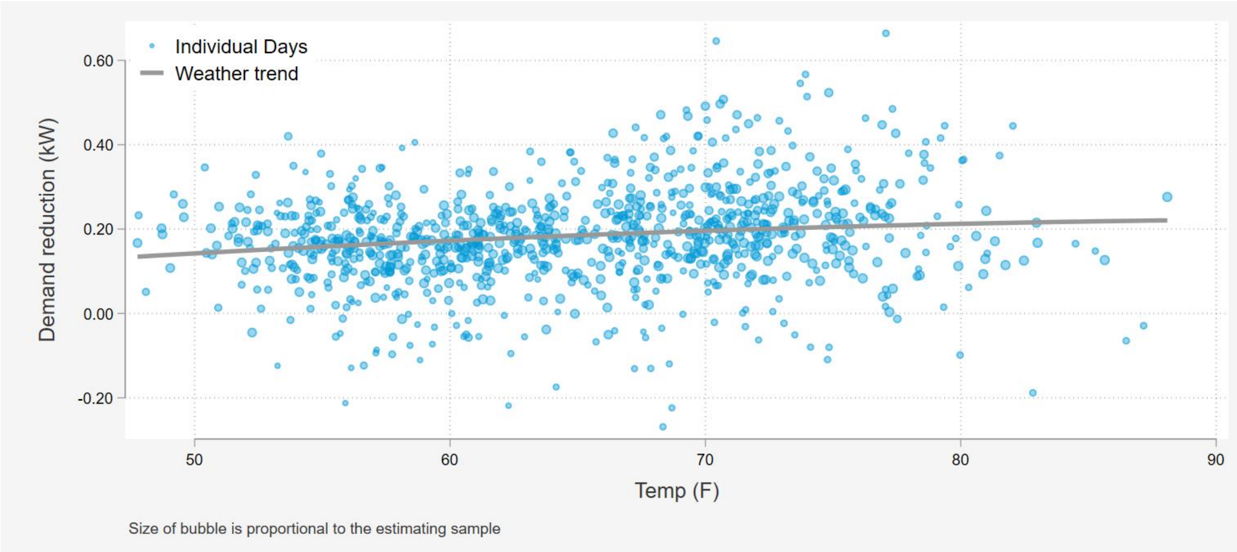
Figure 16: Load Impacts per Site for Key Customer Segments



4.5 WEATHER SENSITIVITY OF LOAD IMPACTS

A key question for residential program is whether the peak period load impacts are weather sensitive. While the electric vehicle rates are designed to encourage charging during super off-peak hours, the rates apply to the energy used by the whole home. Thus, customers have an incentive not only to modulate their electric vehicle charge but to modify demand for other peak period end uses. As part of the evaluation, we estimated the demand reductions for each day and hour of the year using the differences-in-differences technique. Figure 17 shows the relationship between the daily peak period (4-9) load impacts and weather for days after the transition to TOU rates for electric vehicles. In general, the demand reductions grow larger when temperatures are hotter, but the relationship is not pronounced. Customers have an incentive to shift non-EV loads because the rates apply to the whole home, not just the electric vehicle.

Figure 17: Peak Period (4-9 PM) Load Impact Weather Sensitivity



4.6 KEY FINDINGS

- Most new enrollment is occurring on the EVTOU5 rate.
- The number of sites shifting from the EVTOU2 to the EVTOU5 rate is now negligible.
- Customers who enroll on electric vehicle TOU rate decrease demand when prices are higher usage when the prices are lowest. Moreover, the change in load patterns coincides with the enrollment on TOU rates for electric vehicles.
- Customers deliver slightly larger demand reductions on the hotter days.
- On top 10 highest CAISO gross, CAISO net, and SDG&E system load days over the study period, customers reduced demand by 0.28 kW, 0.26 kW, and 0.27 kW per home, on average, over the 4-9 PM peak period. This amounted to reduction in demand between 14%-17% of the household load, and led to over 8 MW in total demand reductions during those days.

5 ELECTRIC VEHICLE TOU EX-ANTE RESULTS

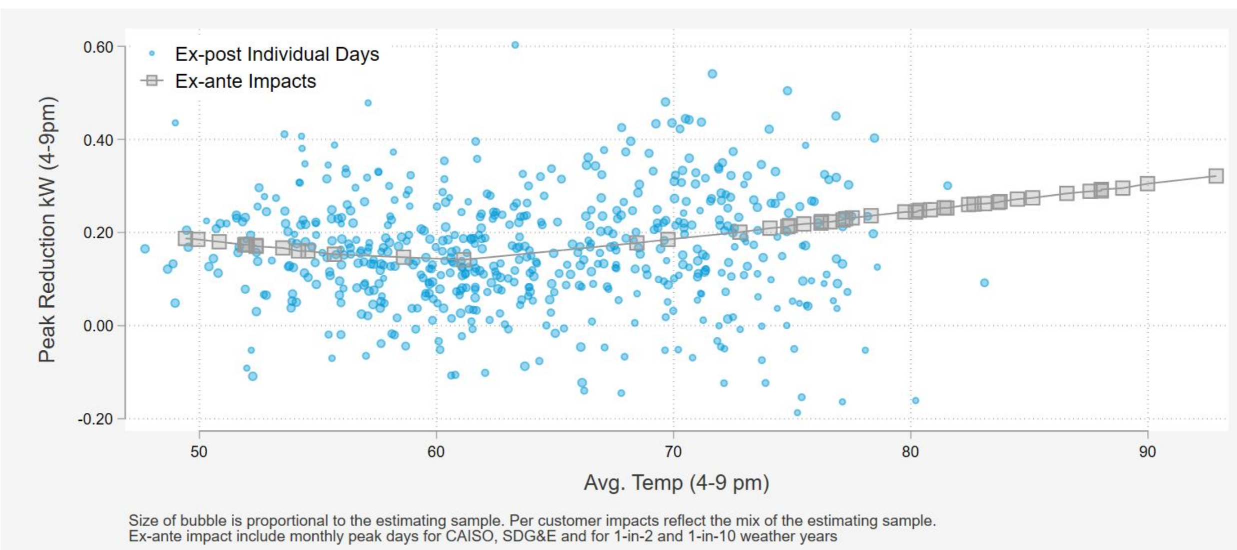
Ex-ante impacts describe the magnitude of program resources available under planning conditions defined by weather. The ex-ante estimates are developed for both SDG&E and California ISO peak conditions under normal (1-in-2) and extreme (1-in-10) peak planning conditions. We estimated ex-ante impacts based on the relationship between demand reductions and weather using the ex-post performance over the analysis period (October 2021 to September 2022) and factored in projected changes in enrollment.

5.1 DEVELOPMENT OF EX-ANTE IMPACTS

The ex-ante impacts were developed by estimating the relationship between weather and demand reductions for customers for who enrolled over the analysis period, had an electric vehicle for the year before they signed onto the rate, and did not install solar or battery storage (a major non-routine event) in the pre-treatment year or the analysis period.

In total, we estimated the relationship between hourly (8,760 hours per year) demand reductions and weather for 4 distinct segments – defined by the rate type (EVTOU2 or EVTOU5) and the presence of rooftop solar. The segmentation allows SDG&E to account for changes in the customer mix, namely that most new participants enroll in EVTOU5, and share of sites with solar is growing. The hourly (8760) pattern of ex-post reductions was analyzed using a multi-variate regression model to estimate ex-ante impact under planning conditions. A separate model was estimated for each segment and hour of day. The model accounts for the effects day of week, and weather. Appendix E includes the output from the model. Figure 18 overlays the per-customer ex-ante impacts for 4-9 pm on top of the ex-post impacts for each individual day over the analysis period.

Figure 18: Ex-ante and Ex-post Per Customer Peak Impacts (4-9 PM)



5.2 OVERALL RESULTS

Figure 19 shows a heat map of the per-customer load reduction by month and hour of day for SDG&E 1-in-2 monthly peak day weather conditions. The results are scaled to reflect the current mix of customers on electric vehicle TOU rates (versus the available estimating sample). Table 10 and Table 11 show the per-customer hourly impacts for each month under CAISO and SDG&E monthly peaking conditions, respectively. The tables are designed to enable the CPUC's Slice-of-Day Resource Adequacy requirements. The estimated reductions are greater on monthly peak days than on average weekdays and larger in hotter months than in cooler ones. The load reductions also coincide with the hours (4-9PM) and months (August and September) when reductions are needed most.

Figure 19: Heat map of Per Customer Ex-ante Load Reductions by Hour and Month

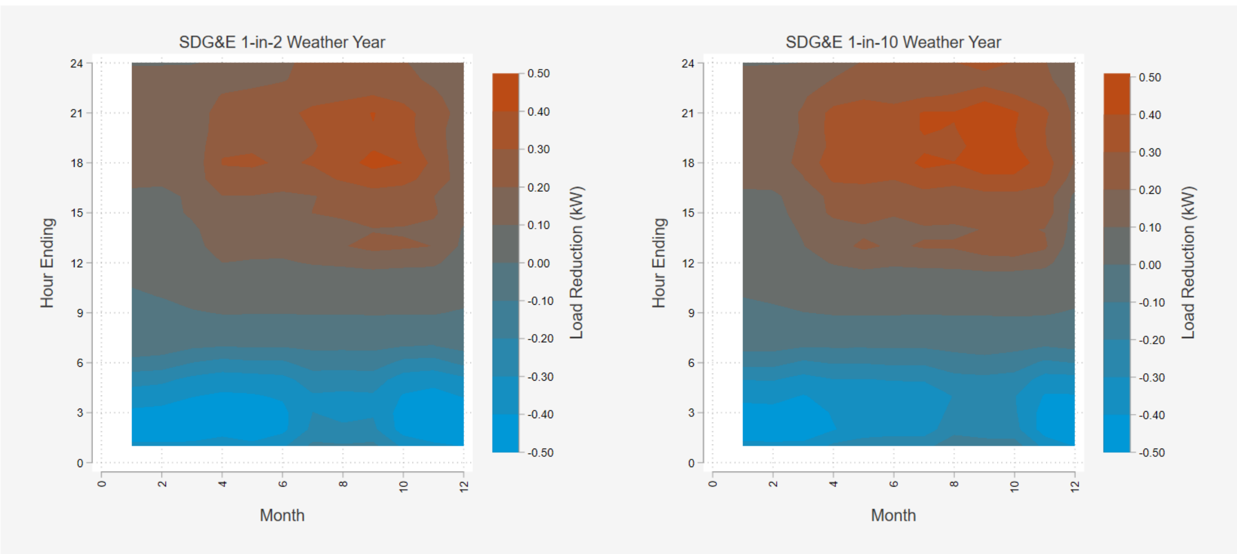


Table 10: Slice of Day Table for CAISO 1-in-2 Weather Year Monthly Peaks (Per Customer Impacts)

Hour Ending	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sep	Oct	Nov	Dec
1	-0.38	-0.39	-0.30	-0.27	-0.28	-0.25	-0.20	-0.17	-0.13	-0.20	-0.34	-0.41
2	-0.44	-0.44	-0.40	-0.41	-0.39	-0.36	-0.30	-0.27	-0.21	-0.32	-0.44	-0.48
3	-0.42	-0.42	-0.41	-0.40	-0.40	-0.38	-0.32	-0.30	-0.26	-0.33	-0.45	-0.46
4	-0.35	-0.35	-0.38	-0.37	-0.38	-0.36	-0.33	-0.31	-0.27	-0.33	-0.41	-0.39
5	-0.27	-0.26	-0.33	-0.31	-0.32	-0.30	-0.27	-0.25	-0.22	-0.28	-0.34	-0.32
6	-0.13	-0.13	-0.21	-0.20	-0.21	-0.19	-0.16	-0.14	-0.13	-0.18	-0.21	-0.18
7	-0.05	-0.05	-0.09	-0.09	-0.09	-0.09	-0.08	-0.08	-0.08	-0.09	-0.09	-0.07
8	-0.06	-0.06	-0.05	-0.05	-0.05	-0.05	-0.05	-0.04	-0.04	-0.05	-0.05	-0.06
9	-0.03	-0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	-0.02
10	-0.02	0.00	0.03	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.01
11	0.01	0.01	0.03	0.03	0.03	0.03	0.03	0.04	0.04	0.04	0.03	0.00
12	0.05	0.04	0.10	0.10	0.11	0.11	0.10	0.13	0.15	0.16	0.13	0.02
13	0.06	0.05	0.15	0.17	0.18	0.18	0.16	0.22	0.24	0.27	0.21	0.05
14	0.06	0.06	0.15	0.16	0.16	0.15	0.16	0.18	0.20	0.22	0.18	0.06
15	0.06	0.06	0.19	0.21	0.22	0.19	0.20	0.22	0.26	0.28	0.23	0.07
16	0.08	0.08	0.18	0.21	0.22	0.19	0.21	0.22	0.26	0.27	0.22	0.08
17	0.13	0.13	0.24	0.30	0.29	0.26	0.28	0.32	0.35	0.37	0.30	0.14
18	0.20	0.18	0.28	0.36	0.35	0.31	0.33	0.39	0.43	0.45	0.31	0.21
19	0.21	0.19	0.27	0.32	0.32	0.29	0.31	0.36	0.41	0.40	0.27	0.21
20	0.22	0.20	0.27	0.32	0.32	0.29	0.31	0.37	0.44	0.39	0.26	0.22
21	0.22	0.20	0.27	0.31	0.31	0.29	0.32	0.38	0.48	0.39	0.26	0.22
22	0.16	0.16	0.22	0.24	0.25	0.24	0.26	0.29	0.34	0.30	0.22	0.17
23	0.14	0.15	0.18	0.20	0.20	0.20	0.22	0.23	0.26	0.24	0.20	0.16
24	0.09	0.09	0.13	0.19	0.19	0.19	0.23	0.26	0.32	0.27	0.15	0.10

Demand Reductions are positive (Blue)
Load increase are negative (Orange)

Table 11: Slice of Day Table for SDG&E 1-in-2 Weather Year Monthly Peaks (Per Customer Impacts)

Hour Ending	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sep	Oct	Nov	Dec
1	-0.38	-0.38	-0.37	-0.28	-0.25	-0.23	-0.23	-0.13	-0.16	-0.15	-0.33	-0.40
2	-0.45	-0.45	-0.47	-0.41	-0.35	-0.35	-0.35	-0.23	-0.25	-0.27	-0.45	-0.48
3	-0.44	-0.43	-0.46	-0.39	-0.37	-0.36	-0.36	-0.27	-0.28	-0.29	-0.44	-0.47
4	-0.37	-0.37	-0.41	-0.37	-0.36	-0.35	-0.35	-0.30	-0.29	-0.30	-0.41	-0.41
5	-0.30	-0.29	-0.34	-0.30	-0.30	-0.29	-0.29	-0.24	-0.23	-0.24	-0.34	-0.34
6	-0.17	-0.17	-0.22	-0.19	-0.19	-0.18	-0.18	-0.14	-0.12	-0.15	-0.22	-0.20
7	-0.07	-0.07	-0.09	-0.09	-0.09	-0.09	-0.09	-0.08	-0.08	-0.08	-0.10	-0.08
8	-0.06	-0.06	-0.06	-0.05	-0.04	-0.04	-0.05	-0.04	-0.04	-0.04	-0.05	-0.06
9	-0.02	-0.02	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	-0.01
10	0.00	0.01	0.04	0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.03
11	0.01	0.01	0.02	0.03	0.04	0.03	0.03	0.04	0.04	0.04	0.03	0.00
12	0.03	0.03	0.06	0.11	0.14	0.12	0.13	0.14	0.16	0.16	0.13	0.01
13	0.04	0.06	0.10	0.17	0.22	0.19	0.21	0.21	0.25	0.27	0.22	0.03
14	0.06	0.07	0.11	0.16	0.18	0.16	0.19	0.18	0.20	0.21	0.20	0.07
15	0.06	0.06	0.14	0.22	0.24	0.21	0.25	0.24	0.27	0.28	0.26	0.06
16	0.08	0.08	0.15	0.23	0.24	0.22	0.26	0.24	0.27	0.27	0.25	0.08
17	0.12	0.13	0.19	0.31	0.32	0.30	0.36	0.34	0.37	0.37	0.33	0.15
18	0.18	0.16	0.23	0.37	0.39	0.35	0.42	0.40	0.47	0.46	0.35	0.19
19	0.19	0.17	0.21	0.33	0.36	0.34	0.39	0.37	0.44	0.41	0.31	0.19
20	0.20	0.16	0.21	0.34	0.37	0.35	0.41	0.39	0.47	0.40	0.30	0.18
21	0.19	0.16	0.21	0.33	0.36	0.34	0.41	0.41	0.51	0.41	0.32	0.18
22	0.16	0.16	0.19	0.25	0.28	0.26	0.29	0.31	0.36	0.31	0.26	0.17
23	0.15	0.15	0.16	0.20	0.22	0.21	0.23	0.24	0.26	0.25	0.21	0.16
24	0.09	0.09	0.10	0.17	0.21	0.21	0.26	0.30	0.34	0.29	0.21	0.10

Demand Reductions are positive (Blue)
Load increase are negative (Orange)

Table 12 shows aggregate ex-ante demand reduction forecasts for an August monthly system peak day. Forecasts are shown under the four weather scenarios identified above. The increase in the demand reductions throughout the forecast years can be explained by the expected growth of electric vehicles and the corresponding growth in electric vehicle TOU rate enrollments. Ex-ante weather conditions are static through the forecast window. There is a small amount of variation in participant-level impacts through the forecast window due to the expected enrollments by rate and solar status. Most future participants are projected to enroll on the EVTOU5 rate.

Table 12: Aggregate August Monthly System Peak Day (SDG&E) Demand Reduction Forecast (MW)

Forecast Year	Enrollment Forecast	SDG&E Weather		CAISO Weather	
		1-in-2	1-in-10	1-in-2	1-in-10
2022	32,258	11.1	12.3	10.4	11.7
2023	53,259	18.7	20.8	17.4	19.7
2024	63,478	22.3	24.8	20.8	23.5
2025	73,409	25.9	28.8	24.2	27.2
2026	81,573	28.8	32.0	26.9	30.3
2027	89,576	31.7	35.2	29.6	33.3
2028	98,014	34.7	38.6	32.4	36.5
2029	106,957	37.9	42.1	35.4	39.9
2030	116,558	41.3	46.0	38.6	43.5
2031	125,101	44.4	49.4	41.4	46.7
2032	133,682	47.4	52.8	44.3	49.9
2033	142,817	50.7	56.4	47.3	53.4

Figure 20 and Figure 21 show the estimated ex-ante load profiles for sites on electric vehicle TOU rates. Both figures show profiles for the August peak day, and both figures use SDG&E weather conditions rather than CAISO conditions. Figure 20 shows profiles under 1-in-2 weather conditions, and Figure 21 shows profiles for 1-in-10. Note that the forecast year shown is 2023. The confidence band for the average impact over the 4-9 pm window is narrower than for individual hours.

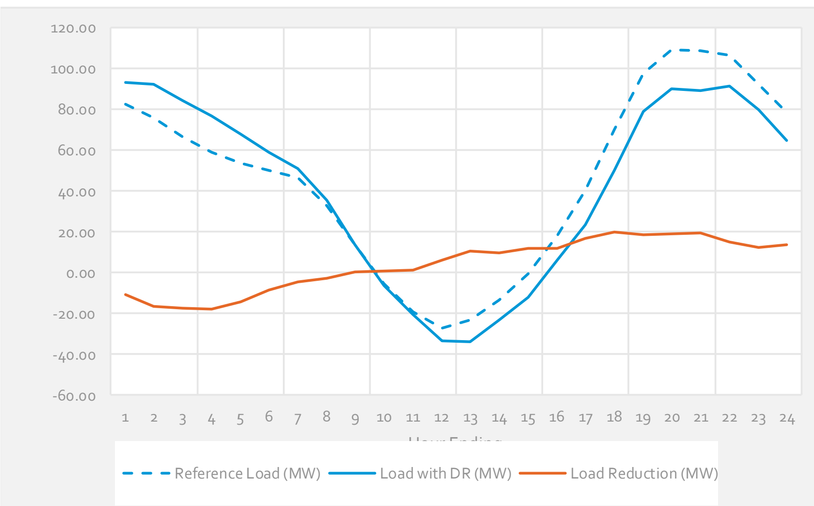
Figure 20: Aggregate Ex-ante Impact for 1-in-2 Weather Conditions, August Peak Day 2023

Table 1: Menu options

Type of Result	Aggregate Total
System (CAISO/SDG&E)	SDG&E
Weather Year	1-IN-2
Forecast Year	2023
Category	All
Subcategory	All
Day type	MONTHLY SYSTEM PEAK DAY
Month	08 Aug

Table 2: Event day information

Total sites	53,259
Daily Max Temp	89.2
Peak Period (4pm-9pm) Impact (MW)	18.67
Peak Period (4pm-9pm) Impact (%)	21.9%



Hour Ending	Reference Load (MW)	Load with DR (MW)	Load Reduction (MW)	% Load Reduction	Avg Temp (°F, Site-Weighted)	Uncertainty Adjusted 5th	Uncertainty Adjusted 95th	Standard Error	T-Statistic
1	82.46	93.05	-10.59	-12.8%	72.4	-28.23	7.04	10.72	-0.99
2	76.04	92.34	-16.30	-21.4%	71.6	-34.94	2.34	11.33	-1.44
3	66.61	84.17	-17.56	-26.4%	71.1	-34.92	-0.19	10.56	-1.66
4	58.91	76.62	-17.71	-30.1%	71.0	-33.61	-1.82	9.67	-1.83
5	53.75	68.05	-14.30	-26.6%	70.9	-27.95	-0.64	8.30	-1.72
6	50.17	58.91	-8.74	-17.4%	70.4	-19.77	2.29	6.71	-1.30
7	46.39	50.95	-4.56	-9.8%	70.5	-13.19	4.08	5.25	-0.87
8	32.97	35.55	-2.59	-7.8%	71.0	-10.62	5.45	4.89	-0.53
9	13.73	13.52	0.21	1.5%	74.6	-8.28	8.70	5.16	0.04
10	-5.56	-6.23	0.67	-12.0%	79.2	-9.66	10.99	6.28	0.11
11	-19.34	-20.73	1.40	-7.2%	84.2	-10.81	13.60	7.42	0.19
12	-27.11	-33.33	6.22	-22.9%	87.4	-5.67	18.11	7.23	0.86
13	-23.15	-33.63	10.48	-45.3%	88.9	-3.16	24.12	8.29	1.26
14	-13.62	-23.10	9.48	-69.6%	89.2	-4.31	23.27	8.38	1.13
15	-0.36	-12.09	11.73	-3303.6%	86.9	-2.30	25.77	8.53	1.38
16	18.01	6.20	11.81	65.6%	87.0	-1.85	25.47	8.30	1.42
17	40.19	23.61	16.58	41.3%	86.9	2.74	30.42	8.42	1.97
18	70.05	50.13	19.92	28.4%	85.7	6.83	33.02	7.96	2.50
19	97.51	79.06	18.45	18.9%	83.0	5.33	31.57	7.98	2.31
20	109.01	90.03	18.98	17.4%	80.3	5.50	32.45	8.19	2.32
21	108.56	89.15	19.41	17.9%	77.2	6.31	32.51	7.97	2.44
22	106.39	91.49	14.90	14.0%	75.4	1.11	28.68	8.38	1.78
23	92.08	79.87	12.21	13.3%	74.1	-1.11	25.52	8.09	1.51
24	78.62	64.79	13.83	17.6%	73.2	0.73	26.93	7.96	1.74
Daily	Reference Load (MW)	Load with DR (MW)	Load Reduction (MW)	% Change	Avg Temp (°F, Site-Weighted)	Uncertainty Adjusted Impact - 5th	Uncertainty Adjusted Impact - 95th	Std Err	T-statistic
	MWh	MWh	MWh		F	5th	95th		
Overall	1112.31	1018.39	93.93	8.4%	78.4	80.52	107.34	8.15	11.52
Peak Hours	425.32	331.98	93.35	21.9%	82.6	80.02	106.67	8.10	11.52

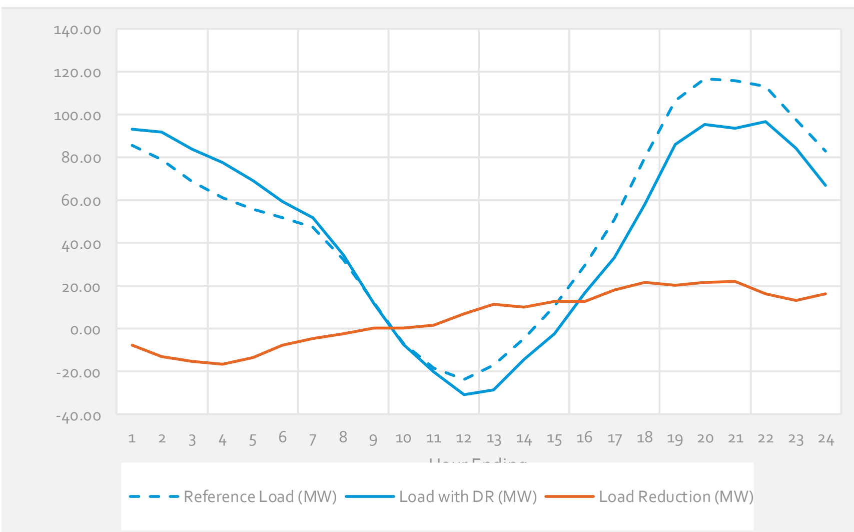
Figure 21: Aggregate Ex-ante Impact for 1-in-10 Weather Conditions, August Peak Day 2023

Table 1: Menu options

Type of Result	Aggregate Total
System (CAISO/SDG&E)	SDG&E
Weather Year	1-IN-10
Forecast Year	2023
Category	All
Subcategory	All
Day type	MONTHLY SYSTEM PEAK DAY
Month	08 Aug

Table 2: Event day information

Total sites	53,259
Daily Max Temp	91.9
Peak Period (4pm-9pm) Impact (MW)	20.78
Peak Period (4pm-9pm) Impact (%)	22.1%



Hour Ending	Reference Load (MW)	Load with DR (MW)	Load Reduction (MW)	% Load Reduction	Avg Temp (°F, Site-Weighted)	Uncertainty Adjusted 5th	Uncertainty Adjusted 95th	Standard Error	T-Statistic
1	85.70	93.38	-7.68	-9.0%	75.8	-25.31	9.95	10.72	-0.72
2	78.91	92.01	-13.10	-16.6%	75.1	-31.74	5.54	11.33	-1.16
3	68.70	83.99	-15.28	-22.2%	74.0	-32.65	2.08	10.56	-1.45
4	61.14	77.64	-16.50	-27.0%	73.2	-32.40	-0.60	9.67	-1.71
5	55.92	69.10	-13.18	-23.6%	72.8	-26.84	0.47	8.30	-1.59
6	51.67	59.33	-7.66	-14.8%	72.8	-18.69	3.37	6.71	-1.14
7	47.32	51.66	-4.35	-9.2%	72.0	-12.98	4.29	5.25	-0.83
8	32.42	34.69	-2.27	-7.0%	74.4	-10.31	5.77	4.89	-0.46
9	12.29	11.90	0.39	3.2%	79.0	-8.09	8.88	5.16	0.08
10	-6.63	-6.97	0.34	-5.1%	84.1	-9.99	10.66	6.28	0.05
11	-18.24	-19.91	1.68	-9.2%	88.8	-10.53	13.88	7.42	0.23
12	-23.80	-30.81	7.01	-29.4%	91.1	-4.89	18.90	7.23	0.97
13	-17.01	-28.39	11.38	-66.9%	91.9	-2.26	25.02	8.29	1.37
14	-4.50	-14.45	9.95	-221.3%	91.5	-3.83	23.74	8.38	1.19
15	10.49	-2.44	12.93	123.3%	91.1	-1.10	26.97	8.53	1.52
16	29.73	16.81	12.92	43.5%	91.0	-0.74	26.58	8.30	1.56
17	51.19	33.18	18.01	35.2%	90.7	4.17	31.85	8.42	2.14
18	80.03	58.27	21.76	27.2%	89.2	8.67	34.85	7.96	2.73
19	106.30	85.88	20.42	19.2%	87.0	7.30	33.54	7.98	2.56
20	116.84	95.33	21.51	18.4%	84.6	8.03	34.98	8.19	2.63
21	115.74	93.55	22.19	19.2%	81.1	9.09	35.29	7.97	2.79
22	113.32	96.89	16.43	14.5%	79.1	2.65	30.22	8.38	1.96
23	97.45	84.33	13.12	13.5%	77.9	-0.19	26.44	8.09	1.62
24	83.17	66.81	16.36	19.7%	77.3	3.27	29.46	7.96	2.06

Daily	Reference Load (MW) MWh	Load with DR (MW) MWh	Load Reduction (MW) MWh	% Change	Avg Temp (°F, Site-Weighted) F	Uncertainty Adjusted Impact - 5th	Uncertainty Adjusted Impact - 95th	Std Err	T-statistic
Overall	1228.16	1101.76	126.39	10.3%	81.9	112.98	139.80	8.15	15.50
Peak Hours	470.10	366.21	103.88	22.1%	86.5	90.56	117.21	8.10	12.82

5.3 COMPARISON TO PRIOR YEAR

Table 13 shows a comparison of vintage year PY2021 and PY2022 ex-ante impacts for the two different weather scenarios at the participant level. All impacts represent monthly peak impact estimates, and SDG&E weather conditions are used. There are three main differences:

1. The PY2022 evaluation relied on all sites that reached a full year of enrollment in electric vehicle time-of-use rates to estimate impacts. In PY2021, the evaluation included all incremental sites that enrolled on the rate over the study period. As a result, the number of sites evaluated for October was small and grows during the study period. The approached creates two challenges. The sample size for early months was inherently small, and there was little data on behavior with TOU rates for the most recent enrollments.
2. The ex-ante weather conditions were updated to reflect the more extreme weather in the most recent decades.
3. The mix of participants analyzed differs slightly because only sites that recently transitioned onto the electric vehicle TOU rates can be evaluated.

The EVTOU5 load impacts are comparable for the core summer months under 1-in-2 and 1-in-10 conditions. There are meaningful differences between the EVTOU2 per customer impacts, however. Those can be attributed to the small estimating sample size in the PY2022 evaluation. Most new participants sign onto EVTOU5 and few sites are left for evaluating EVTOU2 impacts after screening for sites that did not have major changes – add an electric vehicle, install solar or battery – in the year before and after the transition onto the electric vehicle TOU rate. As a practical matter, EVTOU2 per customer impacts have a small effect on the aggregate ex-ante impacts since they are a small and decreasing share of the participants.

Table 13: Comparison of Per Participant Ex-ante Demand Reductions under SDG&E Weather Scenarios (kW)

	PY21 Evaluation				PY22 Evaluation			
	EVTOU5 (n = 1,393)		EVTOU2 (n = 231)		EVTOU5 (n = 702)		EVTOU2 (n = 89)	
	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10
May	0.18	0.35	0.18	0.42	0.23	0.28	0.42	0.59
June	0.21	0.34	0.21	0.40	0.23	0.27	0.40	0.54
July	0.23	0.29	0.25	0.33	0.25	0.30	0.46	0.67
August	0.32	0.32	0.38	0.38	0.27	0.30	0.55	0.63
September	0.38	0.33	0.46	0.39	0.30	0.34	0.66	0.79
October	0.24	0.29	0.26	0.34	0.28	0.31	0.61	0.74

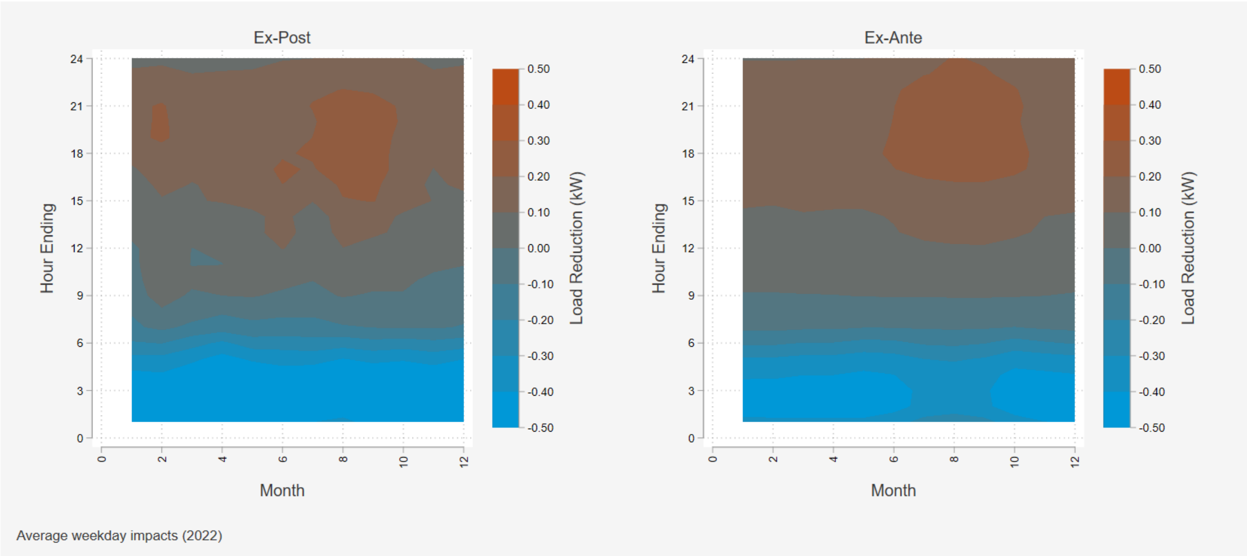
*Per Customer impacts for 2022

5.4 EX-POST TO EX-ANTE COMPARISON

When comparing ex-post and ex-ante, it is important to keep the distinction between the two estimates in mind. Ex-ante impacts are estimates of the future resources available under standardized planning conditions (defined by weather). Ex-post impacts are estimates of what past impacts were given the weather, conditions, and magnitude of resources available. The ex-ante impacts are based on the ex-post impact and weather trends, as shown earlier in Figure 18.

Figure 22 compares the per site ex-post load impacts to the ex-ante load impacts for the average weekday by month and hour. The ex-post load impacts are very similar in magnitude to the ex-ante impact estimates shown in the table. The differences are due to weather. SDG&E experienced the hottest weather conditions in July and October, while the ex-ante standardized weather indicates hotter weather conditions typically occur in August in September.

Figure 22: Comparison of Ex-Post and Ex-Ante Per Customer Impacts under SDG&E peak conditions (2021)



6 VEHICLE GRID INTEGRATION ANALYSIS

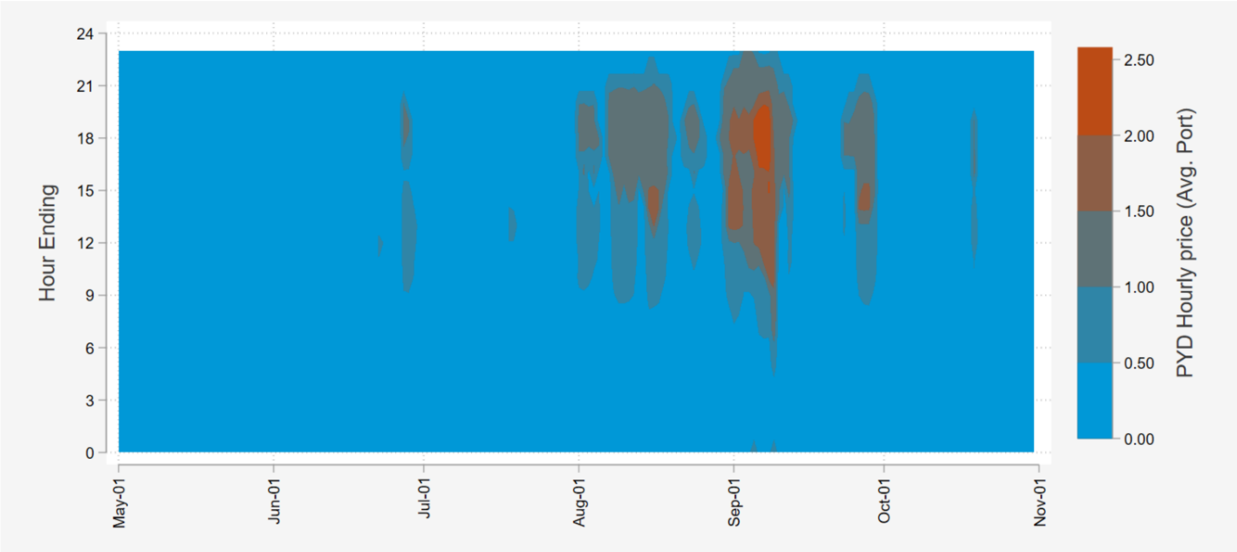
This section focuses on the magnitude of demand reductions delivered by VGI participants for the time frame from October 1, 2022 through September 30, 2022. Through its unique pricing structure, the Vehicle Grid Integration program facilitates multi-family and workplace charging and encourages customers to shift their use from higher priced periods to lower cost periods, but does not directly control the charging behavior or customers or vehicles.

All SDG&E chargers installed at multi-family dwellings and workplaces are billed on SDG&E's Vehicle-Grid Integration electric rate. The unique billing scheme is designed to encourage drivers to charge when there is abundant capacity on the grid. In particular, the Commodity Critical Peak Pricing (C-CPP) and the Distribution Critical Peak Pricing (D-CPP) components can individually add anywhere from $0.60-$0.80 to the hourly volumetric charge. Figure 23 shows a heat map of the VGI prices for the average location by hour and date. SDG&E experienced multiple heat waves and high-priced periods in 2022.

Table 14: SDG&E's Vehicle-Grid Integration Rate Components

Cost Component	Description
Base Delivery Rate	The delivery component is designed to reflect the sunk costs of the transportation system used to deliver energy from where it is used to where it is consumed.
Hourly day-ahead market price	This component reflect supply costs and is based on the California Independent System Operator (CAISO) day-ahead market price for energy supply.
Generation capacity adder	The adder is designed to reflect the costs of generation capacity, which is needed to meet peak demand levels. It is applied to the top 150 system peak hours based on the CAISO day-ahead forecast.
Distribution critical peak pricing adder	The adder is designed to encourage less charging when distribution circuits peak and thereby reduces the risk of overloads and the need for distribution system upgrades. The adder is applied to 200 hours when the circuit is forecasted to peak. This adder is location specific since not all distribution circuits peak at the same time.
An excess supply adder	The excess supply adder is a discount to reflect times when the grid has over-generation and insufficient loads to absorb the supply

Figure 23: Heat map of Vehicle Grid Integration Prices by Date and Hour (Summer 2022)

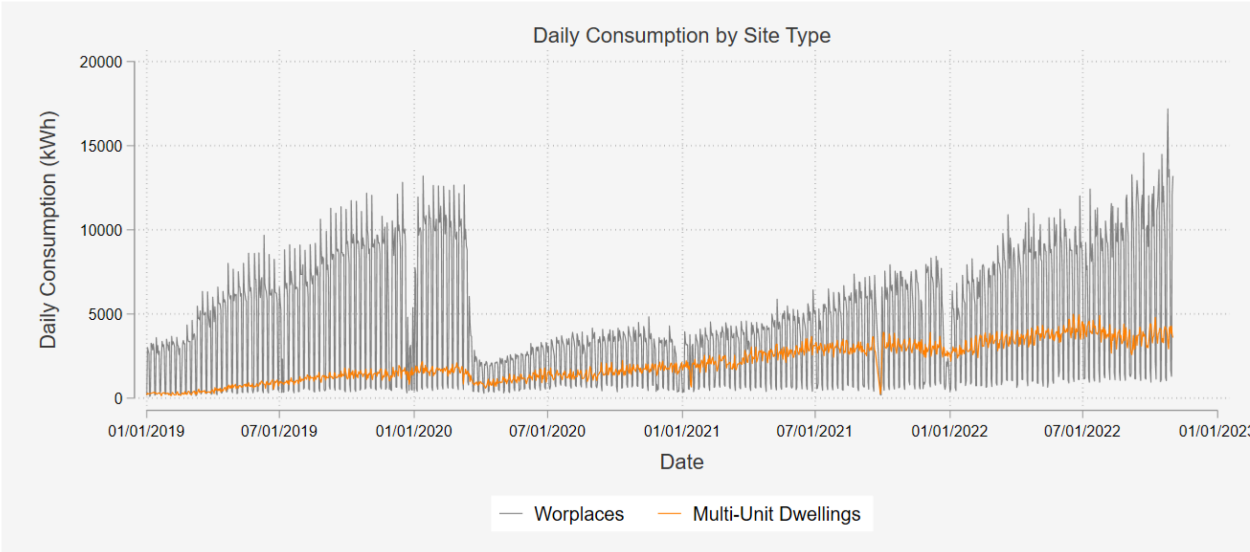


The unique rate design allows us to assess how customers change charging behavior with different price levels. At the same time, the chargers lack a control group since nearly all workplace and multi-family chargers in SDG&E territory are enrolled and have dynamic hourly rates. Thus, the study is observational in nature and relies on quantifying the relationship between customer charging patterns and the dynamic hourly prices. The analysis was implemented using two different frameworks. The first framework relied on estimating the relationship between demand and prices, known as price elasticities. For customers paying for the charging session, we expect demand to decrease as prices increase. The second framework treats periods when the generation and distribution capacity adders are in effect as events. Thus, the analysis is designed to estimate the percent reduction in demand associated with *event* periods. For both frameworks, we separately estimated the impacts for charging ports that did and did not charge the driver and by type of location – multi-family dwelling versus workplace charging.

6.1 COVID-19 EFFECT ON CHARGING PATTERNS AND RECOVERY

COVID-19 strongly impacted the charging patterns of VGI participants at both the Workplace sites and Multi-Unit Dwellings in 2020 and 2021. Figure 24 shows the total daily consumption of charging sessions by Site type since January 1, 2019. Both Workplace and Multi-Unit Dwellings charging sites saw a decrease in EV charging in March 2020. Since then, Workplaces and Multi-Unit Dwellings have rebounded and surpassed pre-pandemic charging. However, the number of electric vehicles has also grown since March 2020.

Figure 24: VGI Charging Trends by Site Type


Daily Consumption by Site Type
Daily Consumption (kWh)
20000
15000
10000
5000
0
01/01/2019
07/01/2019
01/01/2020
07/01/2020
01/01/2021
07/01/2021
01/01/2022
07/01/2022
Date
Worplaces
Multi-Unit Dwellings

6.2 PRICE SENSITIVITY

Table 15 summarizes the price elasticity results. The model specifications and detailed regression outputs are presented in more detail later in this section. There are two main observations. When drivers where charged, they reduced energy use when prices were higher. This is indicated by the negative price elasticity coefficients for multi-family rate to driver (-0.107) and for workplace rate to driver (-0.045). However, when the host paid, the drivers either didn't change behavior or charged more when prices were higher. The charging patterns did not change when multi-family drivers did not have to pay for charging sessions. However, when workplaces rather than drivers paid for the charging sessions, the use of those ports increased when prices were higher.

Table 15: Price Elasticity Summary

Sector	Sites	Ports	Obs	Price Elasticity	Std. Err	t-stat	95% Confidence	
							Lower bound	Upper bound
Multi-family rate to driver	70	754	1,787,751	-0.107	0.008	-14.16	-0.122	-0.092
Multi-family rate to host	1	6	11,538	-0.002	0.009	-0.23	-0.025	0.021
Workplace rate to driver	91	1181	2,082,724	-0.045	0.007	-6.12	-0.059	-0.031
Work place rate to host	49	670	2,159,254	0.059	0.009	6.61	0.042	0.077

CHARGING PATTERNS WITHOUT MODELING

Figure 25 shows average hourly consumption patterns by average daily max price bins for 2022 summer weekdays by the site and billing type. The charging patterns differ for multi-family dwellings and workplaces. Most of the charging for multi-family dwelling sites occurred between dusk and dawn. By contrast, electric vehicle charging at workplaces tended to peak in the morning, near the time when people arrive at offices. The relationship between price and charging patterns is very clear for multi-family dwellings. In general, when prices are high, vehicle charging decreases during the afternoon and evening hours and shift to overnight hours when prices are low.The vehicles are shifting their charging pattern in response to the prices. The price response patterns are more subtle for workplaces. When workplaces charge the driver (far right panel), the overall use is lower on higher priced days (green) across nearly all hours. Rather than shift usage, the drivers appear to bypass charging at the workplace and may instead opt to charge at home. When workplaces do not charge the driver (middle panel), the overall use is actually higher on higher-priced days (green) across nearly all hours. Rather than reduce usage, the drivers appear to be more likely to charge when prices are higher – a hoarding behavior.

Figure 25: Average Consumption by Average Price Bin, Site Type, and Billing Type

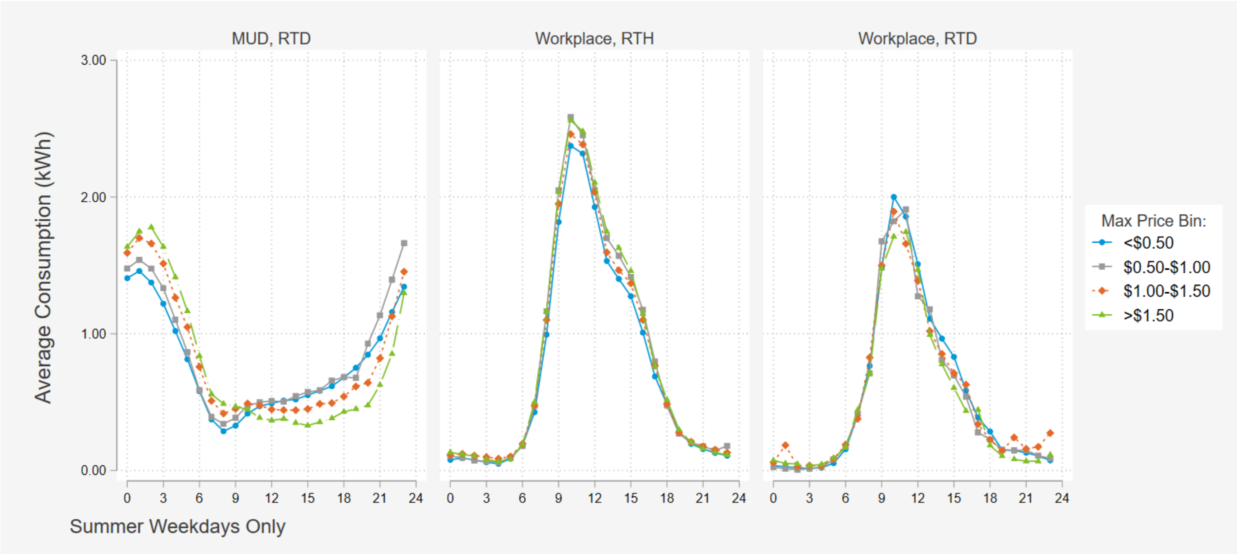
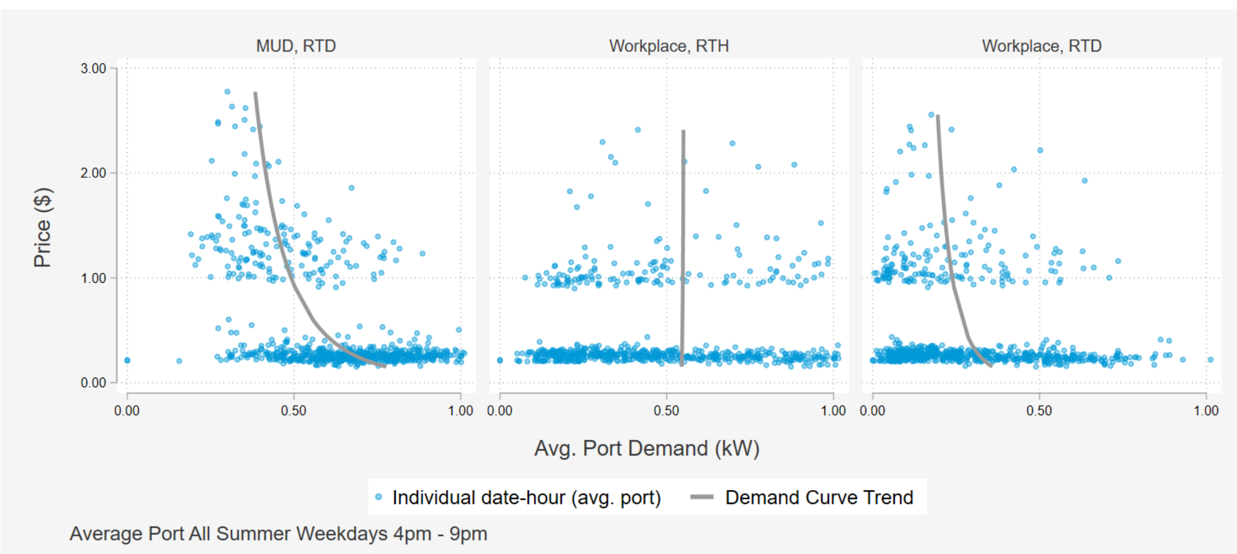


Figure 26 shows the relationship between price and average consumption for the 4-9 pm hours for all summer weekdays. For Multi-Family Dwelling Rate-to-driver charging sites, drivers respond by decreasing charging at higher prices and increasing use at lower prices. The demand curve reflects the price elasticity pattern. The same pattern can be observed at Workplace Rate to Driver charging sites, but the sites are less responsive to prices. However, when the workplace does not charge the driver, the demand is inelastic, meaning the customers do not respond to prices. The gap in prices around $0.50 can be attributed to System and Circuit Critical Peak Pricing Adders as these adders can be as high as $0.60-$0.80/kWh/hour.

Figure 26: Price vs Average Charging Consumption by Site Type and Billing



Regression Results

Table 16 covers the price model specifications. The model was designed to estimate the relationship between demand (kW) and price and controls for the effects of the port location, each date, hour of day, and day of week. We clustered standard errors by port and date.

Table 16: Price Response Regression Specifications

Category	Term	Description
Dependent Variable	ln_kW[1]	Electricity delivered in kW for customer i, in hour h
Price	ln_price	Natural log of hourly price
Fixed Effects	Nozzle ID	Individual Charging Station ID
	Date	Date Variable
	dow	Day of week indicator variables
	hour	Hour of Day indicator variables

Figure 27 shows the regression output for ports that charged the drivers for the charging session. At workplaces, drivers decrease their charging by 0.045% for each 1.0% change in prices. For example, an increase in price from $0.25 to $1.00 per kWh (300% increase) is associated with a 13.5% decrease in demand. At multi-family dwellings, customers were more price responsive. Drivers decreased their charging by 0.107% for each 1.0% change in prices. For example, an increase in price from $0.25 to $1.00 per kWh (300% increase) lead to a 32% decrease in demand. Both results were highly statistically significant.

Figure 28 shows the regression output for ports that <u>did not</u> charged the drivers for the charging session. In essence, the charging session was free to drivers, no matter the actual prices. At workplaces, the results are counter-intuitive and statistically significant. They indicate that drivers charge more at the workplace when prices are higher and they do not have to pay. One potential explanation is drivers are engaging in hoarding behavior - because its free they use more when the prices are higher. Another possible explanation, is that drivers assume prices are also higher at home and thus fill-up at work, effectively shifting usage from home charging to free workplace charging when prices are high. Only one multi-family dwelling with six charging ports provided electric vehicle charging free of charge. The results were not statistically significant due to the small sample size.

[1] The log of kWh relied on an ln(kWh+1) transformation. This helps to handle hours with zero kWh recorded. The log(0) = is undefined. The log(1) = zero.

Figure 27: Price Elasticity Regression Outputs Rate to Driver

Workplace

```
HDFE Linear regression                            Number of obs   =  1,859,669
Absorbing 4 HDFE groups                           F(   1,     399) =      37.51
Statistics robust to heteroskedasticity           Prob > F        =     0.0000
                                                  R-squared       =     0.1963
                                                  Adj R-squared   =     0.1956
Number of clusters (date)     =        400        Within R-sq.    =     0.0007
Number of clusters (nozzleid) =      1,181        Root MSE        =     0.4654

                        (Std. Err. adjusted for 400 clusters in date nozzleid)
------------------------------------------------------------------------------
             |               Robust
      ln_kwh |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    ln_price |  -.0449808    .007344    -6.12   0.000    -.0594186    -.030543
       _cons |      .1272    .010194    12.48   0.000     .1071594    .1472406
------------------------------------------------------------------------------

Absorbed degrees of freedom:
-----------------------------------------------------+
 Absorbed FE | Categories  - Redundant  = Num. Coefs |
-------------+---------------------------------------|
        date |       400         400           0    *|
    nozzleid |      1181        1181           0    *|
        hour |        24           0          24     |
   dayofweek |         7           1           6     |
-----------------------------------------------------+
* = FE nested within cluster; treated as redundant for DoF computation
```

A 1% increase in price led to a 0.045% decrease in consumption

Multi-Unit Dwelling

```
HDFE Linear regression                            Number of obs   =  1,564,772
Absorbing 4 HDFE groups                           F(   1,     399) =     200.51
Statistics robust to heteroskedasticity           Prob > F        =     0.0000
                                                  R-squared       =     0.0710
                                                  Adj R-squared   =     0.0703
Number of clusters (date)     =        400        Within R-sq.    =     0.0019
Number of clusters (nozzleid) =        754        Root MSE        =     0.6112

                        (Std. Err. adjusted for 400 clusters in date nozzleid)
------------------------------------------------------------------------------
             |               Robust
      ln_kwh |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    ln_price |   -.107292   .0075769   -14.16   0.000    -.1221878   -.0923963
       _cons |   .1195303   .0109438    10.92   0.000     .0980156    .1410451
------------------------------------------------------------------------------

Absorbed degrees of freedom:
-----------------------------------------------------+
 Absorbed FE | Categories  - Redundant  = Num. Coefs |
-------------+---------------------------------------|
        date |       400         400           0    *|
    nozzleid |       754         754           0    *|
        hour |        24           0          24     |
   dayofweek |         7           1           6     |
-----------------------------------------------------+
* = FE nested within cluster; treated as redundant for DoF computation
```

A 1% increase in price led to a 0.107% decrease in consumption

Figure 28: Price Elasticity Regression Output, Rate to Host

Workplace

```
HDFE Linear regression                            Number of obs   =  2,078,154
Absorbing 4 HDFE groups                           F(   1,    399) =      43.69
Statistics robust to heteroskedasticity           Prob > F        =     0.0000
                                                  R-squared       =     0.2325
                                                  Adj R-squared   =     0.2321
Number of clusters (date)     =        400        Within R-sq.    =     0.0009
Number of clusters (nozzleid) =        670        Root MSE        =     0.5184

                        (Std. Err. adjusted for 400 clusters in date nozzleid)
------------------------------------------------------------------------------
             |               Robust
      ln_kwh |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    ln_price |   .0594318   .0089914     6.61   0.000     .0417555    .0771082
       _cons |   .3235893   .0126502    25.58   0.000       .29872    .3484587
------------------------------------------------------------------------------

Absorbed degrees of freedom:
-----------------------------------------------------+
 Absorbed FE | Categories  - Redundant  = Num. Coefs |
-------------+---------------------------------------|
        date |       400         400           0    *|
    nozzleid |       670         670           0    *|
        hour |        24           0          24     |
   dayofweek |         7           1           6     |
-----------------------------------------------------+
* = FE nested within cluster; treated as redundant for DoF computation
```

A 1% increase in price led to a 0.059% increase in consumption

Multi-Unit Dwelling

```
HDFE Linear regression                            Number of obs   =     11,538
Absorbing 4 HDFE groups                           F(   1,      5) =       0.05
Statistics robust to heteroskedasticity           Prob > F        =     0.8271
                                                  R-squared       =     0.4039
                                                  Adj R-squared   =     0.3827
Number of clusters (date)     =        361        Within R-sq.    =     0.0000
Number of clusters (nozzleid) =          6        Root MSE        =     0.3977

                          (Std. Err. adjusted for 6 clusters in date nozzleid)
------------------------------------------------------------------------------
             |               Robust
      ln_kwh |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    ln_price |  -.0020402   .0088645    -0.23   0.827    -.0248271    .0207468
       _cons |   .1741773   .0110137    15.81   0.000     .1458657    .2024889
------------------------------------------------------------------------------

Absorbed degrees of freedom:
-----------------------------------------------------+
 Absorbed FE | Categories  - Redundant  = Num. Coefs |
-------------+---------------------------------------|
        date |       361         361           0    *|
    nozzleid |         6           6           0    *|
        hour |        24           0          24     |
   dayofweek |         7           1           6     |
-----------------------------------------------------+
* = FE nested within cluster; treated as redundant for DoF computation
```

No statistical significance that price led to changes in consumption

6.3 EVENT RESPONSE

In addition to price, we investigated charging response to event hours. Event hours were flagged at specific incremental differences from one hour to the next. If there was an increase in the hourly price over $0.45, then the hour was flagged as an event. Each consequential hour was marked an event until price dropped by $0.45.

Table 17 summarizes the event model results. The model specifications and detailed regression outputs are presented in more detail later in this section. The findings are similar to those from the price elasticity analysis. When drivers were charged, they reduced energy use when prices were higher. However, when the host paid, the drivers either didn't change their behavior or charged more when prices were higher.

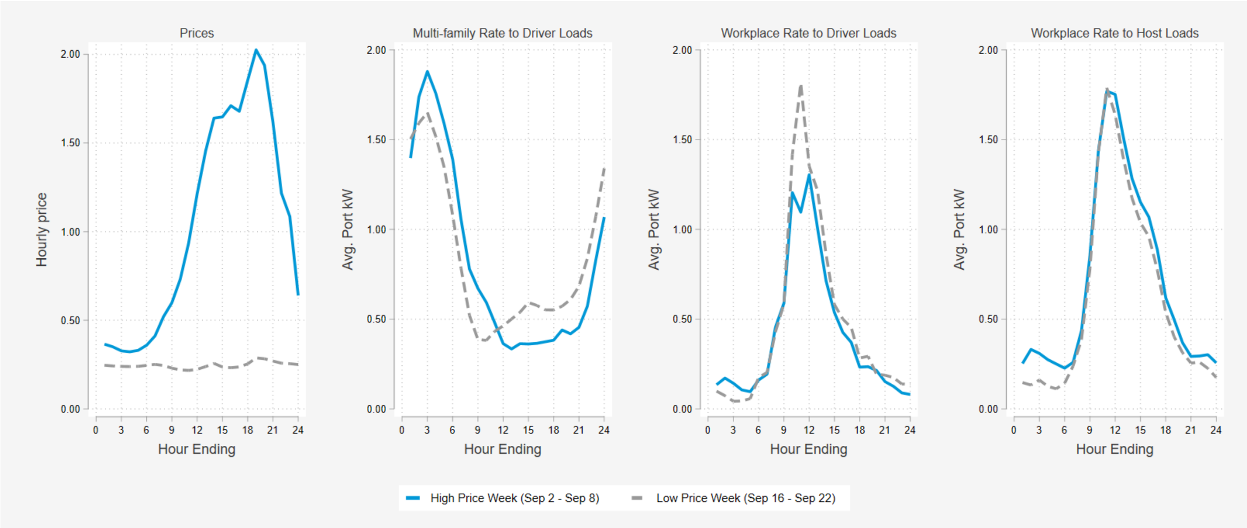
Table 17: Event Response Model Summary

Sector	Sites	Ports	Obs	% Impact	Std. Err	t-stat	95% Confidence Lower bound	Upper bound
Multi-family rate to driver	70	754	1,787,751	-4.14%	0.70%	-5.88	-5.52%	-2.75%
Multi-family rate to host	1	6	11,538	-0.77%	1.46%	-0.53	-4.53%	2.98%
Workplace rate to driver	91	1181	2,082,724	-4.94%	1.15%	-4.29	-7.20%	-2.68%
Work place rate to host	49	670	2,159,254	4.25%	0.92%	4.63	2.45%	6.06%

CHARGING PATTERNS WITHOUT MODELING

One way to assess the patterns is to compare charging patterns during the large heatwave to the closest week with low prices. Figure 29 compares prices and charging loads by type of port for two weeks – September 2 to September 8 and September 16 to September 22. Both weeks span the Friday to Thursday timeframe, minus Mondays, since September 5 was the Labor Day holiday. Overall, there is a distinct surge in prices during the heatwave week while prices were flat in the comparison week. At multi-family dwellings, drivers shifted their EV charging away from the high-priced afternoon and evening hours to lower-priced overnight hours. At workplaces that charge drivers, there was a distinct drop in usage that is pronounced in the mid-morning hours that persists throughout the day, indicating that drivers were less likely to start the charging session.

Figure 29: Comparison of Heatwave to Closest Week with Low Prices



Regression Results

Table 18 covers the price model specifications. The model was designed to isolate the percent change in demand and controls for the effects of the port location, each date, hour of day, and day of the week. We clustered standard errors by port and date. The main difference is that the modeled events, discrete jumps in prices due to the generation and distribution adders rather than estimate price elasticities.

Table 18: Event Response Regression Specifications

Category	Term	Description
Dependent Variable	ln_kWh[2]	Electricity delivered in kW for customer i, in hour h
Event	event	Event hour indicator variable
Fixed Effects	Nozzle ID	Individual Charging Station ID
	Date	Date Variable
	dow	Day of week indicator variables
	hour	Hour of Day indicator variables

Figure 27 shows the regression output for ports that charged the drivers for the charging session. Figure 28 shows the regression output for ports that did not charged the drivers for the charging session.

[2] The log of kWh was calculated by taking 1+ln(kWh). This helps to handle hours with zero kWh recorded. The log(0) = is undefined. The log(1) = zero.

Figure 30: Event Regression Outputs Rate to Driver

Workplace

```
HDFE Linear regression                            Number of obs   =  2,082,724
Absorbing 4 HDFE groups                           F(   1,    399) =      18.44
Statistics robust to heteroskedasticity           Prob > F        =     0.0000
                                                  R-squared       =     0.2016
                                                  Adj R-squared   =     0.2010
Number of clusters (date)     =        400        Within R-sq.    =     0.0005
Number of clusters (nozzleid) =      1,181        Root MSE        =     0.4614

                       (Std. Err. adjusted for 400 clusters in date nozzleid)
```

ln_kwh	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
event	-.0494167	.0115066	-4.29	0.000	-.0720377	-.0267956
_cons	.1942297	.0008743	222.16	0.000	.1925109	.1959485

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs	
date	400	400	0	*
nozzleid	1181	1181	0	*
hour	24	0	24	
dayofweek	7	1	6	

* = FE nested within cluster; treated as redundant for DoF computation

Charging decreased demand by 4.9% during event hours

Multi-Unit Dwelling

```
HDFE Linear regression                            Number of obs   =  1,787,751
Absorbing 4 HDFE groups                           F(   1,    399) =      34.57
Statistics robust to heteroskedasticity           Prob > F        =     0.0000
                                                  R-squared       =     0.0691
                                                  Adj R-squared   =     0.0684
Number of clusters (date)     =        400        Within R-sq.    =     0.0003
Number of clusters (nozzleid) =        754        Root MSE        =     0.6139

                       (Std. Err. adjusted for 400 clusters in date nozzleid)
```

ln_kwh	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
event	-.0413659	.0070356	-5.88	0.000	-.0551975	-.0275344
_cons	.2849286	.0010636	267.88	0.000	.2828375	.2870196

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs	
date	400	400	0	*
nozzleid	754	754	0	*
hour	24	0	24	
dayofweek	7	1	6	

* = FE nested within cluster; treated as redundant for DoF computation

Charging decreased demand by 4.1% during event hours

Figure 31: Price Elasticity Regression Output, Rate to Host

Workplace

```
HDFE Linear regression                          Number of obs   =  2,159,254
Absorbing 4 HDFE groups                         F(   1,    399) =      21.42
Statistics robust to heteroskedasticity         Prob > F        =     0.0000
                                                R-squared       =     0.2321
                                                Adj R-squared   =     0.2317
Number of clusters (date)     =        400      Within R-sq.    =     0.0003
Number of clusters (nozzleid) =        670      Root MSE        =     0.5186

                      (Std. Err. adjusted for 400 clusters in date nozzleid)
------------------------------------------------------------------------------
             |               Robust
      ln_kwh |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       event |   .0425241   .0091872     4.63   0.000     .0244627    .0605855
       _cons |   .2361742   .0007526   313.80   0.000     .2346946    .2376537
------------------------------------------------------------------------------

Absorbed degrees of freedom:
-----------------------------------------------------+
 Absorbed FE | Categories  - Redundant  = Num. Coefs |
-------------+---------------------------------------|
        date |       400         400           0    *|
    nozzleid |       670         670           0    *|
        hour |        24           0          24     |
   dayofweek |         7           1           6     |
-----------------------------------------------------+
* = FE nested within cluster; treated as redundant for DoF computation
```

Charging increased by 4.25% during event hours

Multi-Unit Dwelling

```
HDFE Linear regression                          Number of obs   =     11,538
Absorbing 4 HDFE groups                         F(   1,      5) =       0.28
Statistics robust to heteroskedasticity         Prob > F        =     0.6187
                                                R-squared       =     0.4039
                                                Adj R-squared   =     0.3827
Number of clusters (date)     =        361      Within R-sq.    =     0.0000
Number of clusters (nozzleid) =          6      Root MSE        =     0.3977

                        (Std. Err. adjusted for 6 clusters in date nozzleid)
------------------------------------------------------------------------------
             |               Robust
      ln_kwh |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       event |  -.0077453     .01461    -0.53   0.619    -.0453014    .0298107
       _cons |   .1774634   .0007631   232.57   0.000     .1755019    .1794249
------------------------------------------------------------------------------

Absorbed degrees of freedom:
-----------------------------------------------------+
 Absorbed FE | Categories  - Redundant  = Num. Coefs |
-------------+---------------------------------------|
        date |       361         361           0    *|
    nozzleid |         6           6           0    *|
        hour |        24           0          24     |
   dayofweek |         7           1           6     |
-----------------------------------------------------+
* = FE nested within cluster; treated as redundant for DoF computation
```

No statistical significance that event hours led to changes in consumption

6.4 KEY FINDINGS

- Both multi-family dwelling and workplace drivers who have to pay for their charging (rate to driver) reduce demand when prices are higher.
    - ✓ At workplaces, drivers decrease their charging by 0.045% for each 1.0% change in prices. For example, an increase in price from $0.25 to $1.00 per kWh (300% increase) is associated with a 13.5% decrease in demand.
    - ✓ At multi-family dwellings, customers were more price responsive. Drivers decreased their charging by 0.107% for each 1.0% change in prices. For example, an increase in price from $0.25 to $1.00 per kWh (300% increase) lead to a 32% decrease in demand. Both results were highly statistically significant.
- Customers who do not pay for workplace charging (rate-to-host) tend to increase their use of charge ports when prices are higher. They take advantage of the “free” energy when prices are high.

7 RECOMMENDATIONS

Electric vehicles have the potential to transform the electric grid fundamentally. They are a new, incremental, flexible, and critical load. As the residential electric vehicle market grows, it will impact all aspects of the electric grid. The efforts to ensure electric vehicles are a flexible load over the next few years will be vital as the market share increases. There are over 2.8M vehicles in SDG&E territory and the implications of transportation electrification for the electric grid are large. Moreover, electric vehicles are quickly maturing to an early adopter technology to mass adoption. The transformation is most evident for new vehicles, where electric vehicles constitute 18.8% of the market in San Diego County and 25% of the new vehicle market in Orange County. Thus, it has become increasingly important to provide customers incentives and tools to manage charging to lower bills and reduce use during peak hours.

Key recommendations from the evaluation are:

- **Continue to evaluate and report impacts for all sites that reached a full year of experience with electric vehicle time-of-use rates (1st year impacts).** Using a rolling enrollment approach leas to few incremental sites in October but grows during the study period. The approach creates two challenges, however. First, the sample size for early months is inherently small. Second, there is little data regarding behavior with TOU rates for sites that enroll towards the end of the study period. Shifting to analyzing sites that reached a full year of experience under TOU rates addresses these challenges. It ensures a large enough number of sites are analyzed each month and ensures we fully factor in the behavior of each new enrollment.
- **Remove from the analysis sites whose enrollment on electric vehicle TOU rates coincides with the introduction of the electric vehicle into the home.** Electric vehicles fundamentally change whole home load patterns and consumptions levels. Without sufficient data on EV charging patterns without the EVTOU5 and EVTOU2 rates, it is impossible to estimate the TOU effect on load patterns. The same applies to the installation of solar or battery storage. They fundamentally change whole home loads, and sites with installations over the study period (or the pre-intervention year) should be removed from the analysis.
- **Assess whether SDG&E can incorporate California Department of Motor Vehicle (DMV) registration data to identify control sites** – sites with electric vehicles that are not enrolled on EVTOU5 or EVTOU2. The DMV makes vehicle registration data available for public use but with limitations on how it is used and requirements regarding public notices and data security. While algorithms to identify electric vehicles using AMI data are helpful, vehicle registration data is a better source of information.
- **Consider offering automated demand management to customers who enroll on electric vehicle rates.** We recommend SDG&E make the offer immediately after a customer enrolls on an electric vehicle rate. Vehicle charging now can be managed via direct communication with vehicle on-board computers, an approach known as telematics, which does not require installations of devices. Currently, SDG&E does not directly manage vehicle charging. Instead, the TOU rates encourage customers to shift load from higher-price peak hours to lower-price

off-peak and super off-peak hours. A TOU rate is considered a “passive” form of demand response, leaving it up to the customer to take action. Not all customers modify the vehicle settings to charge during super-offpeak periods. Telematics can be used to incorporate customer preferences, set default charge settings, lower customer bills, and reduce grid impacts via managed charging. It can also be used to actively respond to grid prices and events, making the electric vehicle a truly flexible load. The use of telematics fundamentally shifts the paradigm from behavioral prices response to prices-to-devices that respond based on user preference settings.

- **Consider modifying the building blocks used for ex-ante impacts.** Currently, the ex-ante impacts are based on four types of sites, customers on EV-TOU-5 and EV-TOU-2 with and without solar. Few new sites are enrolling on EV-TOU-2 and most new enrollment are on EV-TOU-5. As a result, the EV-TOU-2 analysis relies on an estimating sample that is small. For future years, we recommend that SDG&E build its ex-ante forecast based on sites on electric vehicle TOU rates with and without solar, eliminating the distinction between EV-TOU-5 and EV-TOU-2.
- **The Power-Your-Drive charging app has a key feature – the ability to restrict charging when prices exceed a threshold – that is rarely used. We recommend changing the default settings**. To enable this feature, customers have to change the default settings and define a price threshold to automate the response. We recommend an A/B test to assess how changing the default settings affects charging behavior. In specific, we recommend testing a default that avoids charging when prices are high (above $0.50/kWh), provides users a push notice that prices are high, and allows drivers to “charge anyway” via the push of a button..