FINAL REPORT
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2021 Load Impact Evaluation of San Diego Gas and Electric's Electric Vehicles Time-of-Use (TOU) Rates

Prepared for San Diego Gas & Electric

By Demand Side Analytics, LLC

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ABSTRACT

This report summarizes the findings of the San Diego Gas and Electric's (SDG&E) EV-TOU Rates and the Pilot Power Your Drive (PYD) Program. Over 2.4M 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, over 31,000 electric vehicles and 19,000 plug-in hybrid electric vehicles (PHEV) are registered in SDG&E territory. SDG&E offers electric vehicle time-of-use rates that encourage customers to shift usage away from peak hours and charge when electricity costs are low (super-offpeak hours). In total, SDG&E has enrolled roughly 25,000 homes on electric vehicle rates. These customers decreased demand during the 4-9 pm peak hours by approximately 15% (6.5MW) and increased energy use during the lowest price hours. The change in load patterns coincides with the enrollment on TOU rates for electric vehicles. 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 with a focus 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. SDG&E deployed 3,118 charging ports at 254 locations. A total of 35% of the chargers are located in multi-family dwellings, and 36% of sites are located in disadvantaged communities. The use of workplace and multi-family dwelling charges dropped in 2020 with the onset of the COVID pandemic and started to rebound in 2021. SDG&E rates for PYD charging stations are based on a combination of hourly market prices, distribution cost recovery, and adder 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 dropped by 2.8% and 3.2%, respectively, during high price events.

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1 EXECUTIVE SUMMARY

This report summarizes the findings of the San Diego Gas and Electric's (SDG&E) EV-TOU Rates and the Pilot Power Your Drive (PYD) Program. The EV-TOU rates are voluntary Time of Use rate programs structured to provide savings in electric bills of Electric Vehicle (EV) drivers while encouraging charging during times when the grid historically has more capacity. The PYD program is a unique dynamic rate structure designed to have pricing react to grid conditions in real-time and aims to provide enrolled customers with the tools necessary to respond to live 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 and aim to increase access to EV adoption. This report aims to provide an overview of each program's history, methods, and impacts and a summary of the Program Year 2021 ex-post and ex-ante impacts for 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 electric vehicle rate with sub-metering for the charger, which is not included in the evaluation SDG&E has over 25,000 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 peak at 40.3 MW, and participants curtail demand by 6.78 MW on average. For the top 5 load days for SDG&E Gross loads, participant loads peak at 45.1 MW, and participants can curtail demand by 6.43 MW on average.

Table 1: Ex-post Load Impacts on Highest System Load Days

						Avg. Customers (kW)		Aggregate (MW)		
System	Month	Sample[1]	New Accounts	Total Accounts	Daily avg. temp[2]	Reference Load	Load Reduction	Reference Load	Load Reduction	% Change
CAISO Gross Loads	Top 05 load day(s)	1,635	6,586	23,872	75.0	1.69	0.28	40.30	6.78	16.8%
	Top 10 load day(s)	1,635	6,586	23,872	75.3	1.61	0.23	38.45	5.56	14.5%
	Top 20 load day(s)	1,711	6,586	23,872	74.9	1.55	0.21	36.93	5.02	13.6%
CAISO Net Loads	Top 05 load day(s)	1,711	7,209	24,511	75.4	1.75	0.26	42.85	6.38	14.9%
	Top 10 load day(s)	1,711	6,586	23,872	74.6	1.60	0.25	38.26	5.92	15.5%
	Top 20 load day(s)	1,716	6,586	23,872	74.3	1.52	0.21	36.38	4.91	13.5%
SDG&E Gross Loads	Top 05 load day(s)	1,711	7,209	24,511	77.0	1.84	0.26	45.08	6.43	14.3%
	Top 10 load day(s)	1,716	6,586	23,872	76.7	1.75	0.19	41.89	4.63	11.1%
	Top 20 load day(s)	1,716	6,586	23,872	76.0	1.68	0.20	40.22	4.80	11.9%

[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 PYD KEY FINDINGS

SDG&E's Power Your Drive program was designed in response to the Vehicle-Grid Integration Roadmap presented by the California ISO (CAISO). The program was developed to reduce barriers to electric transportation such as charging infrastructure. SDG&E was approved to install over 3,000 charging ports, and as a result, over 3,100 charging ports owned and operated by SDG&E have been installed across its service territory.

Table 2: Summary of PYD Key Findings

Topic	Findings
Did performance differ across the two different charging sites (Workplaces vs. 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
Did the COVID pandemic affect the magnitude of customer response?	Behavior changes related to COVID19 presented a challenge for the PYD program. There was a fundamental change in charging patterns, with a large drop when stay-at-home orders were enacted in March 2020. Since then charging at all sites has been climbing. The relationship between price and charging patterns at Multi-Unit Dwellings and at Workplaces with rate to host billing did not change in a statistically significant way. However, Workplaces with rate to driver billing saw a decrease in price response during high periods, potentially due to a different mix of drivers at the workplace than in pre-COVID times.

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 Power Your Drive (PYD) pilot. 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: estimate the demand reductions that were delivered in 2021 and to quantify the magnitude of demand reductions available during peaking conditions used for planning.

Time of use 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. The EVTOU2 and EVTOU5 rates are whole premise rates. SDG&E also has a small number of homes with as sub-meter for the electric vehicle charger, which is 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.
- **Power Your Drive Pilot Vehicle Grid Integration Rate.** The Pilot was designed to reduce greenhouse gas ("GHG") and criteria pollutants 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 3,040 charging ports at 254 locations. The PYD 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:
  - ✓ 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 rate is a 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 the energy transportation system and distribution circuit peaks and thereby reduces the risk of overloads and the need for distribution system upgrades.
- ✓ An excess supply adder. The excess supply adder is actually 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 PYD pilot. In specific, it details the key research questions, summarizes 2021 grid conditions, discusses the electric vehicle TOU rates and historical participation, presents the Power Your Drive 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 Power Your Drive 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?

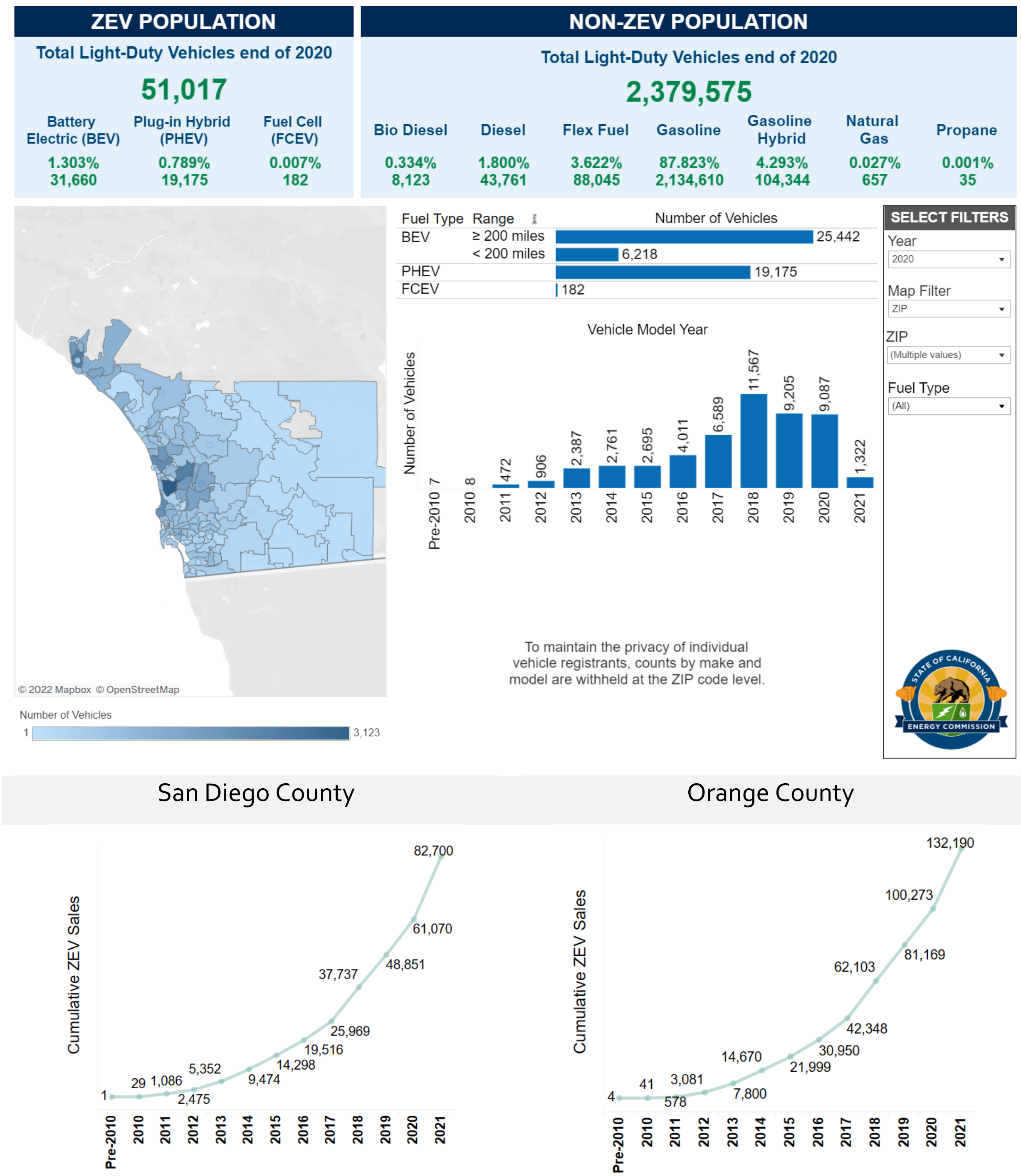
2.2 KEY FACTS ABOUT ELECTRIC VEHICLES IN SDG&E

Electric vehicles have the potential to transform the electric grid fundamentally. As the residential electric vehicle market saturation 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 2020, over 2.4M vehicles were 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, over 31,000 electric vehicles and 19,000 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.

Figure 1: Electric Vehicle Population in SDG&E Territory (2020)



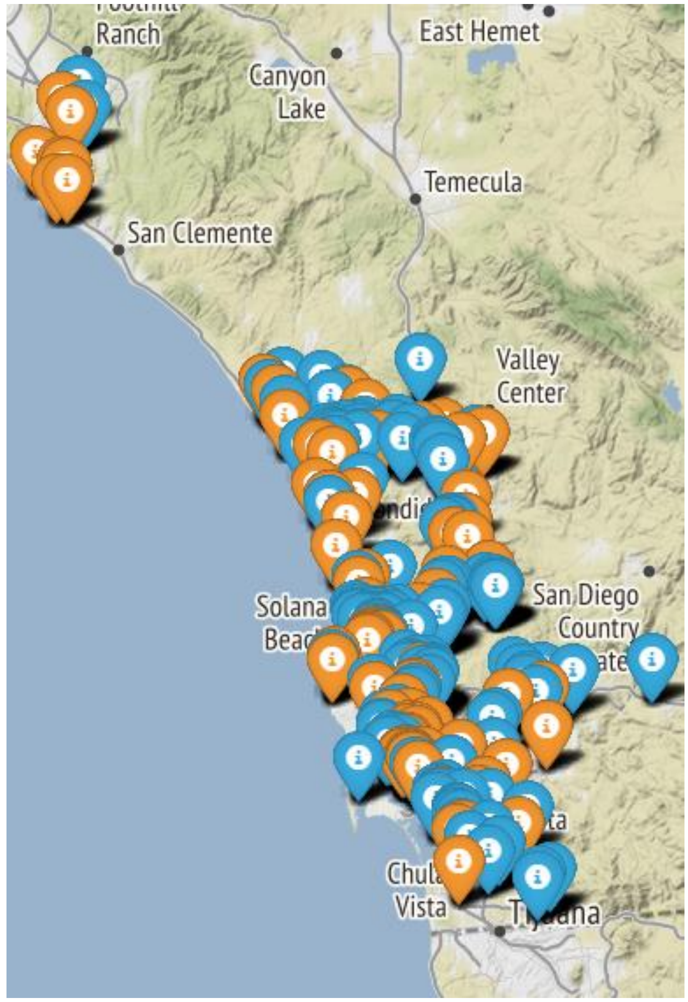
Source: California Energy Commission (2022). New ZEV Sales in California. Data last updated December 31, 2021. Retrieved February 27, 2021, from https://www.energy.ca.gov/zevstats

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 3,118 charging ports at 254 locations. A total of 35% of the chargers are located in multi-family dwellings, and 36% of sites are located in disadvantaged communities.

Figure 2: SDG&E Power Your Drive Electric Vehicle Chargers

KEY FACTS

- There are 237 Sites, 3,118 Stations, and 3,612 actively enrolled drivers.
- 176 Sites are registered for rate-to-driver billing, representing 74% of the total.
- 70% of all stations are installed at rate-to-driver sites.
- 94% of the 3,612 actively enrolled drivers are enrolled at rate-to-driver sites.
- Of the 936 drivers enrolled in Rate-to-Host programs, 89 are registered as a fleet or private shuttle vehicles.



2.3 2021 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 PYD prices encourage customers to shift usage to lower-priced hours when the electric grid is not peaking.

Figure 3 shows the hourly load pattern for the ten highest load days for SDG&E, CAISO, and CAISO net loads. Over the study period (Oct 2020-Sep 2021), peak demands were lower than in historical years: SG&E peaked at 4,162 MW, CAISO peaked at 43,615 MW, and CAISO net loads peaked at 41,776 MW. Figure 4 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 SG&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 5 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 3: SDG&E and CAISO Top Ten Peak Load Days (Oct 2020-Sep 2021)

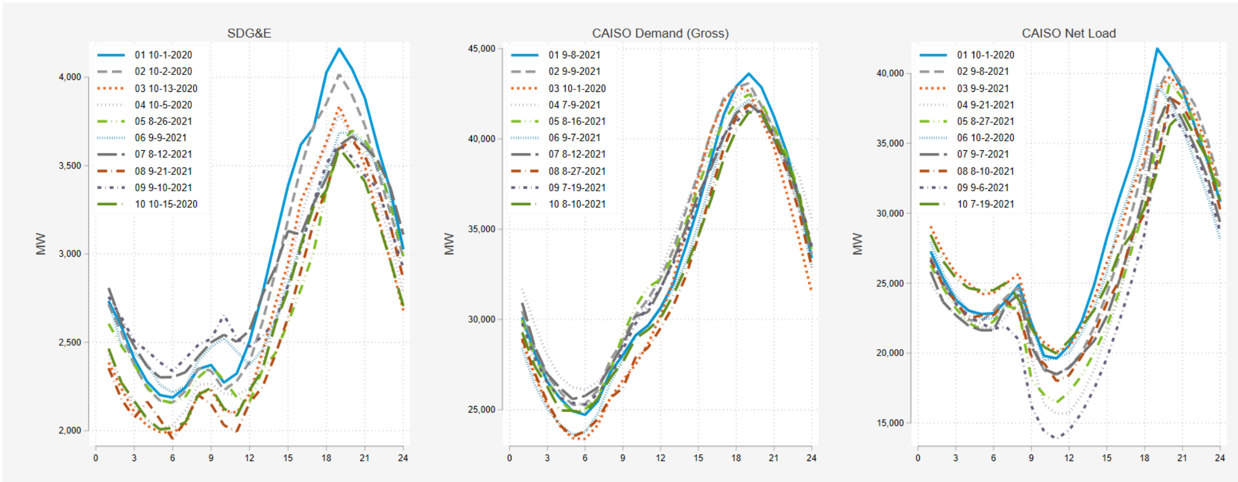


Figure 4: Normalized Load Duration Curves (Oct 2020-Sep 2021)

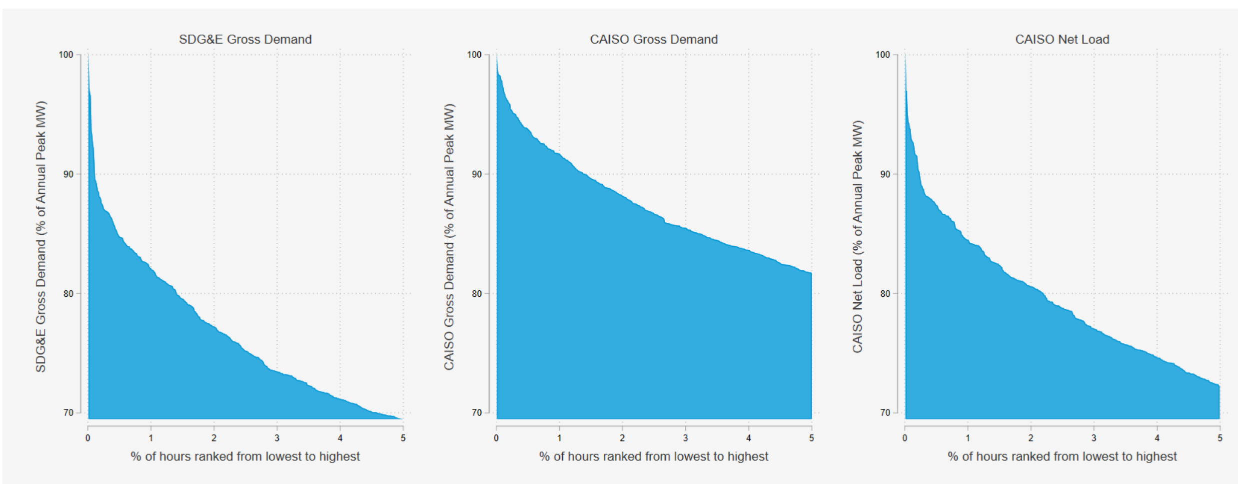
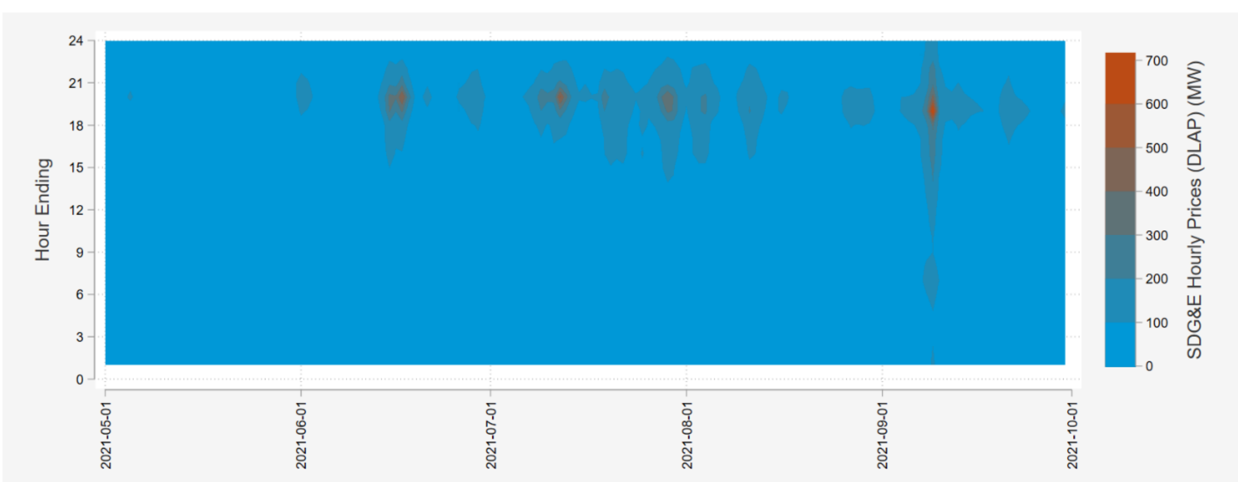


Figure 5: SDG&E Hourly Electricity Market Prices

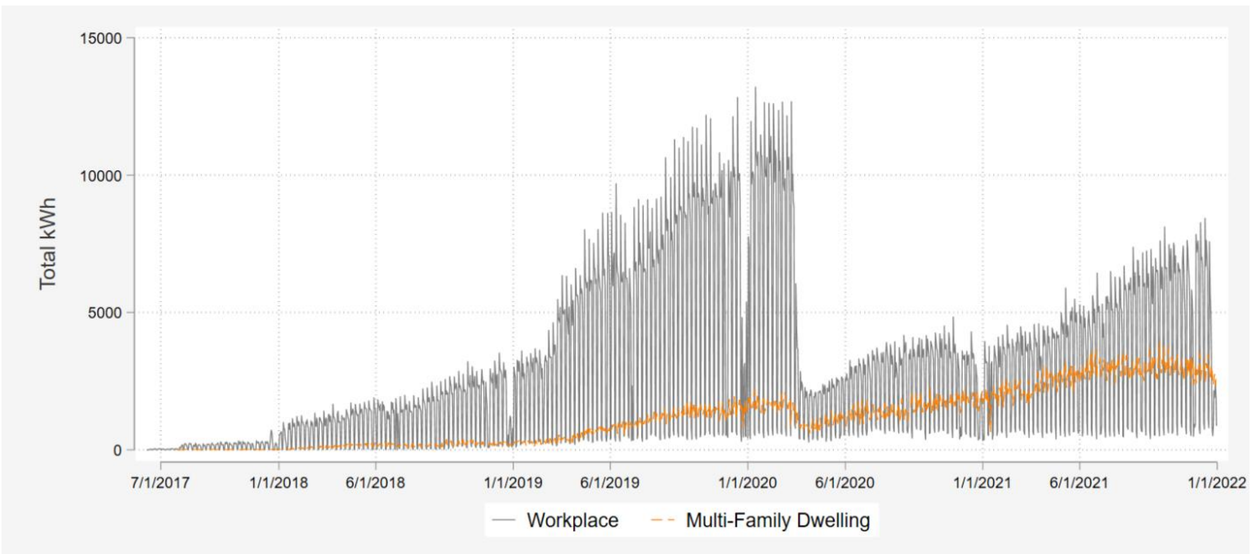


2.4 COVID EFFECTS

In March of 2020, the COVID19 pandemic created mass shutdowns across the United States and fundamentally altered driving and commuting patterns. Many businesses across the SDG&E territory were closed, and residents were subject to quarantine and stay-at-home orders. The guidelines for lockdowns changed throughout 2020 and 2021, and the behavioral impacts of these lockdowns are apparent in customer consumption and charging patterns.

As shown in Figure 6, the PYD program experienced a significant drop in charging at both workplace stations and multi-family dwelling stations when the lockdown orders were enacted in March 2020. Since then, residential charging appears to have rebounded to pre-pandemic levels. Workplace charging remains below pre-pandemic levels, but it has been increasing as vaccines become available and participants start to return to some pre-pandemic activity level.

Figure 6: Total Daily Charging kWh by Workplace and Multi-Family Dwelling Stations



These abrupt consumption changes present a challenge to estimating both EV-TOU and PYD program impacts, including:

- The potential for confounding COVID effects with price effects. The magnitude of the COVID effect on charging is much larger than the price response effect. Moreover, California experienced a prolonged heatwave and energy shortages in the summer of 2020, leading to a concentration of higher prices that also coincides with the COVID deep quarantine in 2020.
- The potential of mixing up changes in charging behavior due to the recovery with price effects. In specific, driving and charging has increased over time as SDG&E customer have increased access to vaccines and learned to live with COVID. But in general, there is more vehicle charging in periods later in 2021 than in periods earlier in 2021.

The evaluation used two primary tools to disentangle COVID effects from price effects. First, we included time effects, which control for the impact of conditions unique to each date that are common across all sites. Second, we included the google community index data for San Diego and Orange County. The indexes use phone data to track changes in how and where people spend time at the county level and specifically tracks the change in time at workplaces, homes, and transit hubs.

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 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 definitive data about EV ownership for homes already signed onto TOU rates for electric vehicles. Thus, 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. Thus the analysis requires careful attention to other large changes in energy use that can be confounded with electric vehicle impacts. Therefore, 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, we used an algorithm focused on changes in household max demand to identify the timing of adoption of the electric vehicle.
- The effects of the COVID-19 pandemic on underlying load patterns from 2020 onward. The COVID pandemic fundamentally changed commute patterns, and those effects are expected to persist. From an evaluation standpoint, it poses a fundamental challenge since the driving behavior is evolving as the pandemic effects subside and California reopens. Thus, 2020 driving and charging behavior is inadequate for establishing a credible baseline for how customers would have behaved without TOU rates. Given COVID's impact on commute patterns, a control group is essential to the evaluation.
- Rolling enrollments. 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. To address this issue, we took four steps:
    1. Use a common identifier, a match id, for each participant and its matched control. This allowed us to ensure that participants and controls were treated equally and that participants were paired with their corresponding control
    2. Standardize the analysis to the 365 days before and 365 days after the participant's enrollment on the EV TOU rate.
    3. Only keep observations with before and after data for both the participant and its associated control for the same day of the year. This ensured that any difference-in-differences analysis was balanced.

4. Analyze like days. For example, when we estimated impacts for the top 10 highest system load days, we included only the top 10 highest load days in the year before and after EV TOU enrollment. This ensures the difference in differences adjustment was calibrated to correct day types.

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 full population of incremental participants, along with a matched control group, was analyzed. The evaluation focused only on incremental sites that enrolled on EVTOU in 2021 and excluded sites who had a change in electric vehicle, solar, or battery status that coincided with the study period. The evaluation include 25% of the new enrollments because it is common for customer to enroll on TOU rates for electric vehicles when they first get their vehicle.
2. **Data included in the analysis**	The analysis included up to year of pre and 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 control group of customers with electric vehicles but who were not on SDG&E's TOU rates for electric vehicles. The process 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 will also identify the date the electric vehicle(s) arrived at the household. Once control candidates with electric vehicles had been identified, we matched customers who enrolled on TOU rates for electric vehicles in 2021 using 2020 (pre-treatment) hourly AMI data. The matching on pre-treatment loads used Euclidian distance matching and matched were selected only from customers with similar electric vehicle propensity scores.
4. **Evaluation Method**	Panel regression difference-in-differences with fixed customer effects, daily time effects, and weather were used to isolate the load impact. Regressions were run for like days. For example, when we estimated impacts for the top 10 highest system load days, we included only the top 10 highest load days in the year before and after EV TOU enrollment. This ensures the difference in differences adjustment was calibrated to correct day types.
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 at identifying the control pool with electric vehicles, but not on TOU rates for electric vehicles. For the evaluation, we used a standard difference-in-differences panel regression with customer fixed effects, date-time effects, and weather explanatory variables.
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.

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 with 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 (EV TOU5 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 customers reference loads and load impacts with an incremental forecast of enrollment on EV TOU rated developed by SDG&E.

Methodology Component	Demand Side Analytics Approach
3. Accounting for changes in the participant mix	The ex-ante load impacts accounts for changes in the participant mix across the two main rate types – EVTOU2 and EVTOU5 – and due to 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 POWER YOUR DRIVE METHODOLOGY

The unique rate design and billing approach created for the Power Your Drive Program makes it challenging to evaluate the program traditional to the California Load Protocols. Customers enroll in this rate specifically for access to SDG&E's PYD charging infrastructure. The only consumption is through EVs plugging into the charging infrastructure.

Evaluation Approach

The key challenges that affect the evaluation approach are:

- The effect of COVID-19 on EV charging patterns: COVID-19 presented a distinct challenge in teasing out charging behavior changes related to COVID-19 waves from program price response. To address shifts in where and how often EV owners are charging as a result of stay at home orders, we included time effects in the regressions, which control for the impact of condition unique to each date that are common across all sites.
- Estimating a Counterfactual and identifying an otherwise applicable tariff: The PYD program rates are developed specifically for the cost of charging at those EV stations. Drivers enroll in the program, and either that station will apply the bill directly to their SDG&E bill, or the station host will have chosen to cover the cost of charging at that site. Additionally, the VGI rate is a dynamic hourly rate that adjusts with the grid conditions. Due to the uniqueness of the VGI rate, there is no direct tariff comparison for this Rate as in other DR and TOU programs.
- Session-based consumption data: Customer demand and billing on the PYD program only comes from driver charging sessions on PYD charging stations. This makes it difficult to assign a specific 'customer' when evaluating the program. We decided to aggregate charging kWh across charging sessions to the station level and included all hours without charging. This method creates a full picture of overall charging patterns and trends without leaving out critical information indicated by non-charging hours.

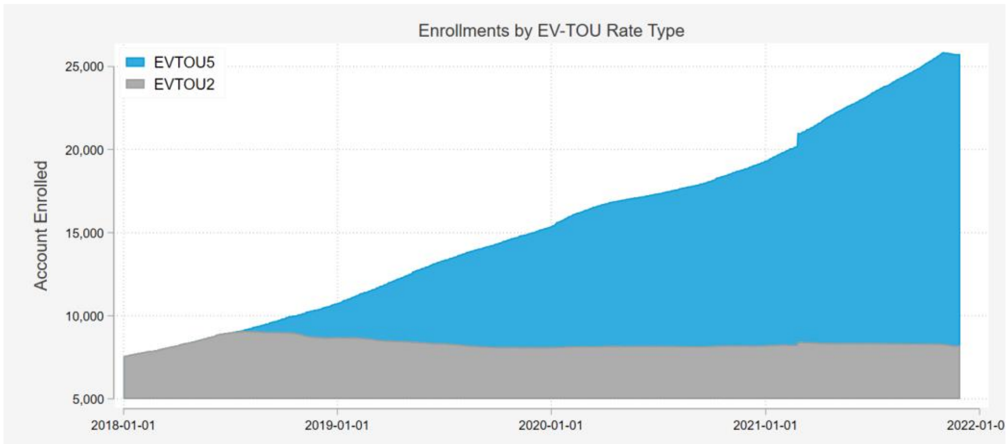
Methodology Component	Demand Side Analytics Approach
1. Population or sample analyzed	Charging data from all PYD charging sessions from the program's launch in 2017 through December 2021 were provided for evaluation. We analyzed charging

		sessions from January 2019 through December 2021. Until 2019, the program was still quickly bringing stations online and aggressively enrolling participants.
2.	**Data included in the analysis**	For the PYD 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 station with multiple fixed effects. Regressions were run in relation to both Price response and Event responses. The Price model related price changes on the program to hourly charging kWh. 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 treated station ID, date, day of week and hour as categorical regressors, and captured Station ID and date as fixed effects in each panel.
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

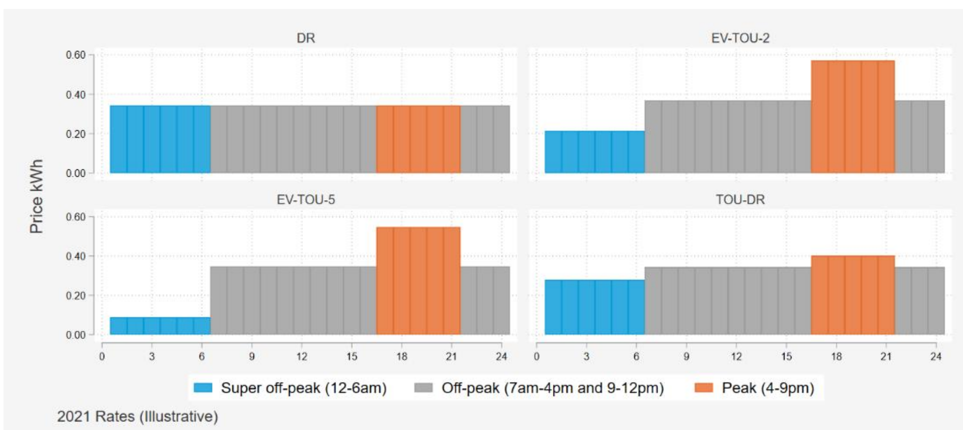
This section focuses on the magnitude of demand reductions delivered by incremental EV TOU participants for the time frame from October 1, 2020 and September 2021. SDG&E has two primary whole premise rates for electric vehicles, EVTOU2 and EVTOU5. There are also a small number of customers on the legacy EVTOU rate which applies to just the charging for the vehicle at the customer's home. They encourage customers to shift their use from higher priced periods to lower cost periods, but do not directly control the charging behavior or customers or vehicles.

Figure 7: Enrollments by EV TOU Rate type



Since mid-2018 most electric vehicles have signed onto the EVTOU5 rates. In addition, some of the customers have transitioned from the EVTOU2 rate to EVTOU5. Overall, SDG&E has signed over 25,000 homes onto electric vehicle TOU rates. For context, SDG&E has 31,000 full battery electric vehicles, and 19,000 plug-in hybrid vehicle in its territory.

Figure 8: Residential Rates Sumer 2021 Prices

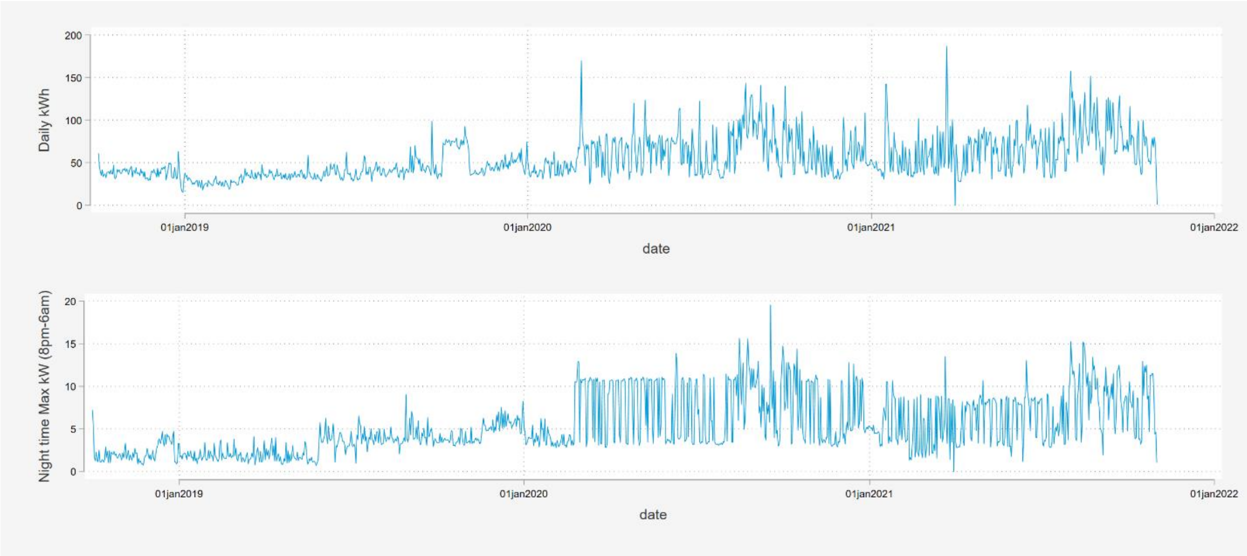


Participation in the rates is voluntary and customers selected the TOU rates for electric vehicles over the default rate flat domestic rate (DR) and the default TOU rate (TOU-DR) that applies to roughly 60% of SDG&E customers. Notably, the EVTOU2 and EVTOU5 rates have higher peak prices (4-9 PM) and lower super-off-peak peak prices (12-6AM). The super-off-peak prices are particularly low for the EVTOU5 rates, but are offset by a higher non-volumetric fixed price component.

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 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 plot are not based on regression model, but reflect the raw data. 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 increases 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).

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. Since customers enroll at different times, the plots are standardized based on the 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. The change in energy usage for participants 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.

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

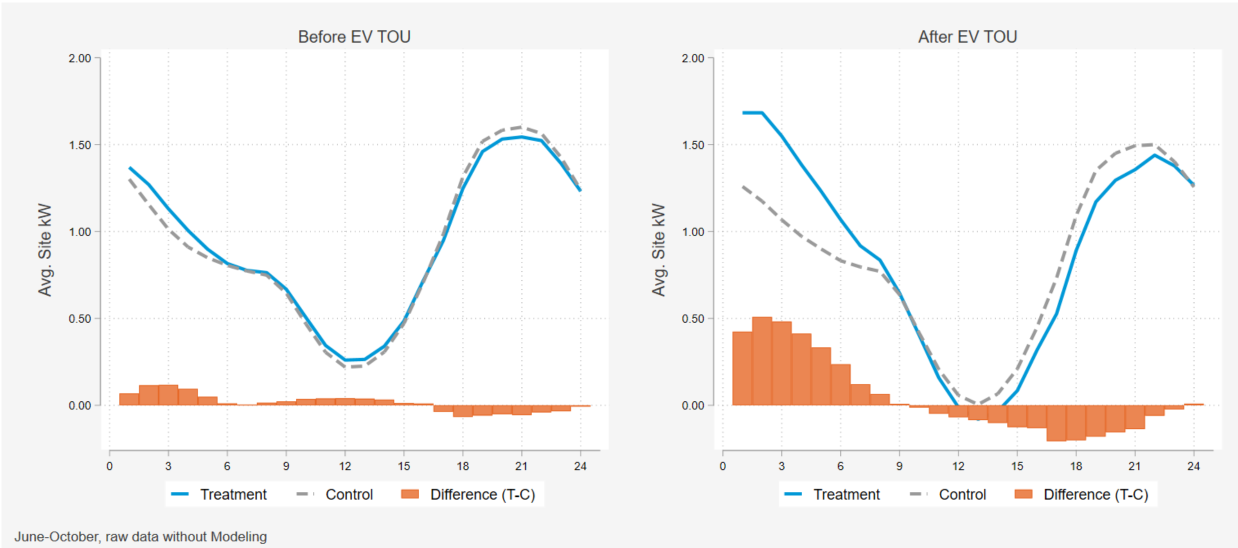
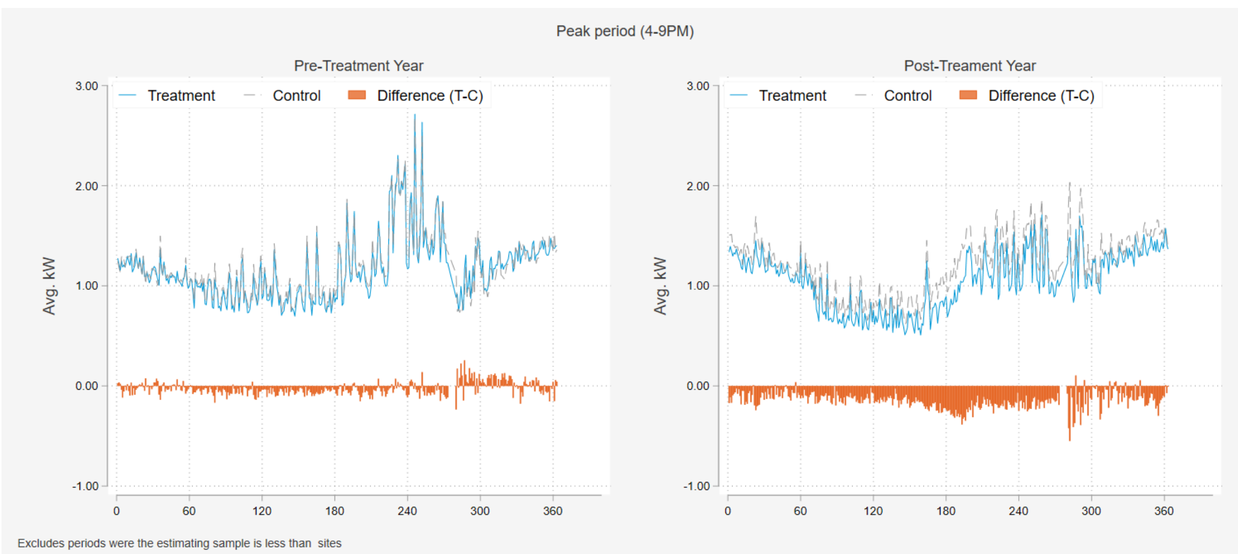


Figure 11: Standardized Time Series Before and After TOU rate for electric vehicles



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 3 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 12 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 4 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 12: Hourly Load Impacts on Top Highest Load Days by System

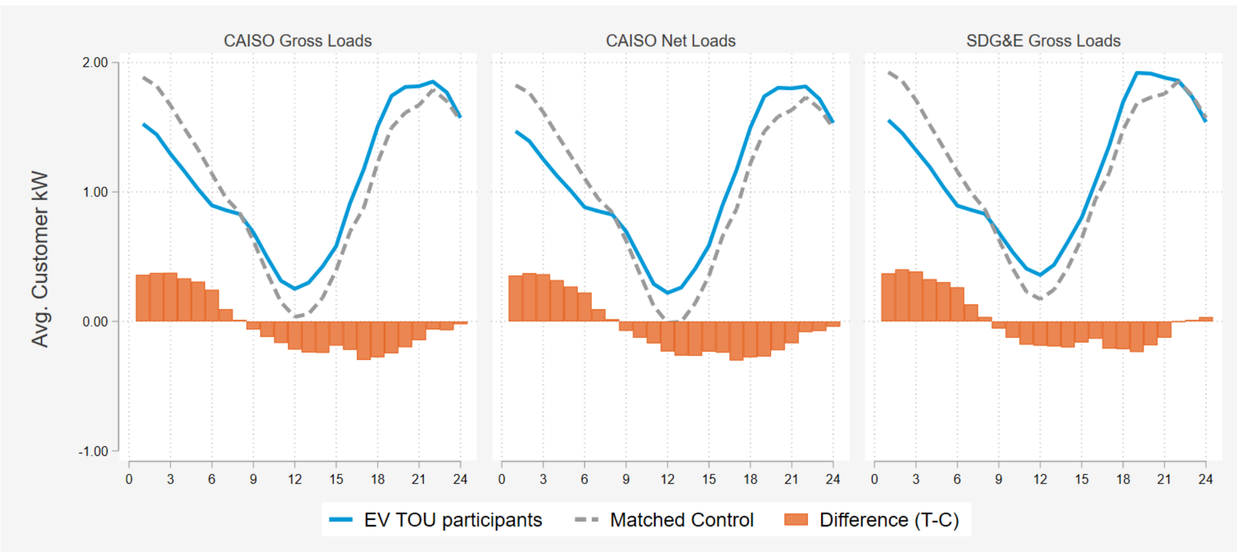


Table 4: Ex-post Load Impacts on Highest System Load Days

						Avg. Customers (kW)		Aggregate (MW)		
System	Month	Sample[1]	New Accounts	Total Accounts	Daily avg. temp[2]	Reference Load	Load Reduction	Reference Load	Load Reduction	% Change
CAISO Gross Loads	Top 05 load day(s)	1,635	6,586	23,872	75.0	1.69	0.28	40.30	6.78	16.8%
	Top 10 load day(s)	1,635	6,586	23,872	75.3	1.61	0.23	38.45	5.56	14.5%
	Top 20 load day(s)	1,711	6,586	23,872	74.9	1.55	0.21	36.93	5.02	13.6%
CAISO Net Loads	Top 05 load day(s)	1,711	7,209	24,511	75.4	1.75	0.26	42.85	6.38	14.9%
	Top 10 load day(s)	1,711	6,586	23,872	74.6	1.60	0.25	38.26	5.92	15.5%
	Top 20 load day(s)	1,716	6,586	23,872	74.3	1.52	0.21	36.38	4.91	13.5%
SDG&E Gross Loads	Top 05 load day(s)	1,711	7,209	24,511	77.0	1.84	0.26	45.08	6.43	14.3%
	Top 10 load day(s)	1,716	6,586	23,872	76.7	1.75	0.19	41.89	4.63	11.1%
	Top 20 load day(s)	1,716	6,586	23,872	76.0	1.68	0.20	40.22	4.80	11.9%

[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 AND MONTHLY AVERAGE DAY

Table 5 shows the reference loads and load impacts by rate period for the monthly peak day of each month. The demand reductions are generally larger for hotter months. Customers reduced demand by 0.54 kW per site (24.4%) in October 2020, when SDG&E experienced its highest peak demand, and reduced demand by 0.26 kW per site in September 2021, when CAISO experienced it highest demand levels. Because the evaluation focuses on incremental sites only, the number and mix of customers differed between October 2020 and September 2021. In specific, the estimating sample for October 2020 is smaller. Table 6 shows the reference loads and load impacts by rate period for the average day of each month, which show a similar pattern.

Figure 13 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. Figure 14 show a similar visual for the average day of each month.

Figure 13: Ex-post Monthly Peak Day Hourly Load Impacts

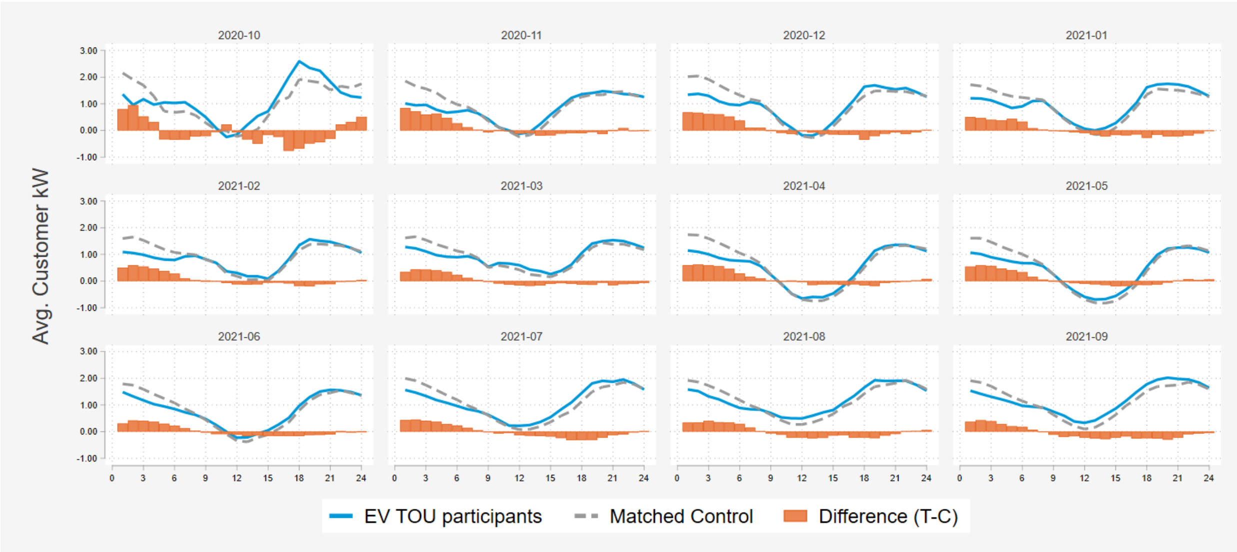


Figure 14: Ex-post Monthly Average Day Hourly Load Impacts

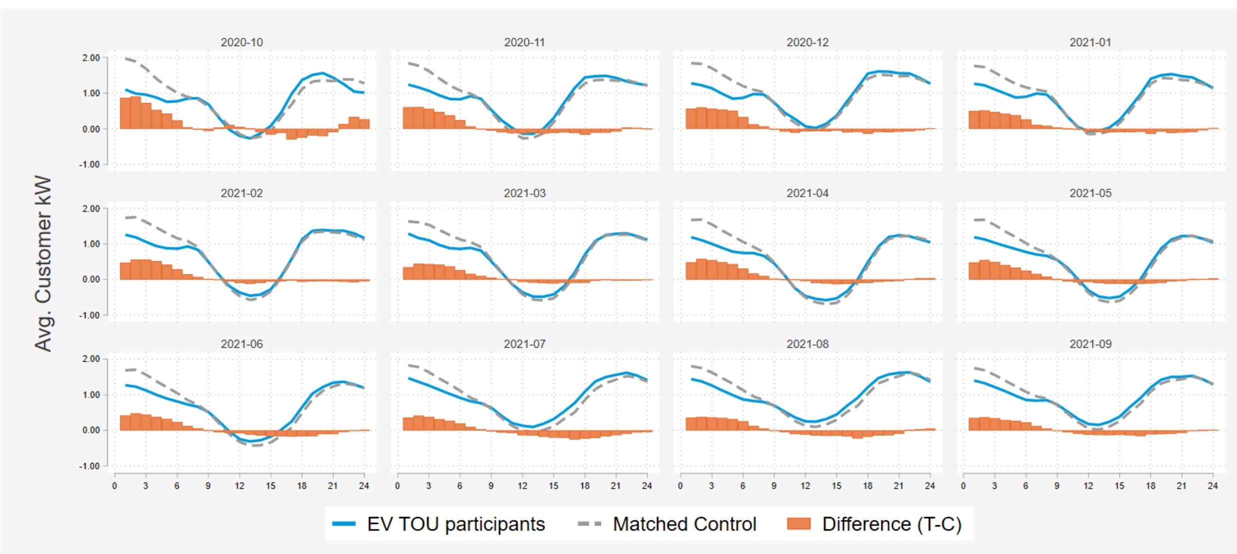


Table 5: Ex-post Monthly Peak Day Load Impacts by Rate Period

				Avg. Customers (kW)		Aggregate (MW)		
Rate Period	Month	Total Accts	Daily avg. temp[1]	Reference Load	Load Impact	Reference Load	Load Impact	% Change
Peak (4-9 PM)	2020-Oct	18,556	79.0	2.20	0.54	40.86	9.96	24.4%
	2020-Nov	18,911	66.8	1.38	0.08	26.10	1.54	5.9%
	2020-Dec	19,349	54.3	1.53	0.18	29.51	3.56	12.1%
	2021-Jan	19,879	49.5	1.57	0.21	31.27	4.09	13.1%
	2021-Feb	20,651	55.8	1.34	0.14	27.72	2.90	10.5%
	2021-Mar	20,948	53.6	1.22	0.12	25.60	2.49	9.7%
	2021-Apr	21,582	72.8	0.93	0.12	20.10	2.52	12.5%
	2021-May	22,110	69.3	0.80	0.09	17.72	2.06	11.6%
	2021-Jun	22,729	73.7	1.17	0.14	26.62	3.15	11.9%
	2021-Jul	23,255	75.8	1.63	0.26	37.84	6.13	16.2%
	2021-Aug	23,872	77.5	1.75	0.19	41.66	4.46	10.7%
	2021-Sep	24,511	76.5	1.84	0.26	45.19	6.34	14.0%
Off-peak (6AM-4PM and 10PM-12AM)	2020-Oct	18,556	81.4	0.68	0.07	12.59	1.25	9.9%
	2020-Nov	18,911	71.5	0.58	0.05	10.88	0.90	8.2%
	2020-Dec	19,349	58.8	0.63	0.06	12.15	1.12	9.2%
	2021-Jan	19,879	51.2	0.71	0.09	14.11	1.77	12.5%
	2021-Feb	20,651	57.6	0.66	0.04	13.60	0.73	5.3%
	2021-Mar	20,948	54.4	0.75	0.08	15.80	1.76	11.1%
	2021-Apr	21,582	74.6	0.17	0.02	3.68	0.43	11.6%
	2021-May	22,110	69.3	0.13	0.04	2.94	0.84	28.6%
	2021-Jun	22,729	72.6	0.48	0.06	10.97	1.46	13.3%
	2021-Jul	23,255	76.8	0.80	0.07	18.72	1.73	9.2%
	2021-Aug	23,872	79.0	0.95	0.09	22.61	2.10	9.3%
	2021-Sep	24,511	77.9	0.96	0.14	23.46	3.49	14.9%
Super off-peak (12-6AM)	2020-Oct	18,556	64.2	1.09	-0.32	20.24	-5.88	-29.1%
	2020-Nov	18,911	56.7	0.85	-0.59	15.99	-11.17	-69.9%
	2020-Dec	19,349	44.3	1.17	-0.58	22.70	-11.16	-49.2%
	2021-Jan	19,879	48.6	1.05	-0.42	20.80	-8.40	-40.4%
	2021-Feb	20,651	52.5	0.93	-0.46	19.31	-9.58	-49.6%
	2021-Mar	20,948	48.7	1.07	-0.36	22.33	-7.63	-34.1%
	2021-Apr	21,582	57.0	0.94	-0.52	20.37	-11.22	-55.1%
	2021-May	22,110	56.5	0.87	-0.49	19.13	-10.79	-56.4%
	2021-Jun	22,729	62.8	1.13	-0.34	25.79	-7.71	-29.9%
	2021-Jul	23,255	67.9	1.27	-0.36	29.42	-8.46	-28.8%
	2021-Aug	23,872	69.0	1.26	-0.35	30.10	-8.26	-27.4%
	2021-Sep	24,511	66.2	1.26	-0.31	30.83	-7.63	-24.7%

[1] Participant weighted average temperature. SDG&E maps all customers to eight weather stations.

[2] To reduce noise, the top 3 system load days were included in the analysis for each month

Table 6: Ex-post Monthly Average Day Load Impacts by Rate Period

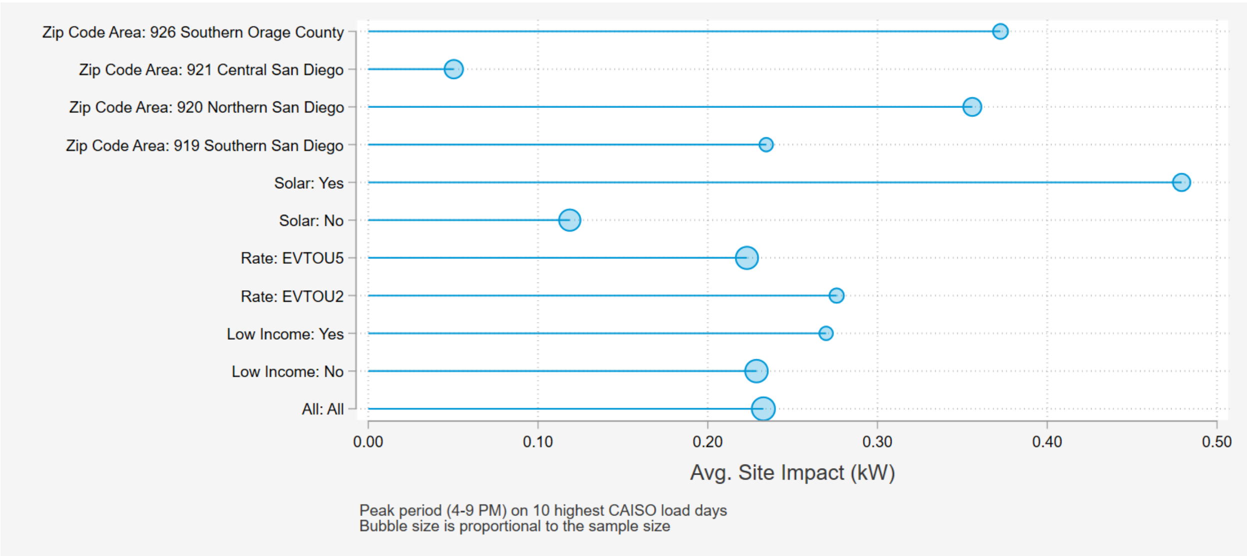
Rate Period	Month	Total Accts	Daily avg. temp[1]	Avg. Customers (kW) Reference Load	Avg. Customers (kW) Load Impact	Aggregate (MW) Reference Load	Aggregate (MW) Load Impact	% Change
Peak (4-9 PM)	2020-Oct	18,556	68.5	1.37	0.21	25.45	3.83	15.1%
	2020-Nov	18,911	58.0	1.40	0.12	26.40	2.21	8.4%
	2020-Dec	19,349	55.5	1.50	0.10	28.96	1.93	6.7%
	2021-Jan	19,879	55.3	1.38	0.11	27.39	2.12	7.7%
	2021-Feb	20,651	56.4	1.17	0.05	24.14	0.96	4.0%
	2021-Mar	20,948	57.8	0.90	0.05	18.94	1.08	5.7%
	2021-Apr	21,582	62.6	0.77	0.07	16.60	1.52	9.1%
	2021-May	22,110	63.2	0.74	0.08	16.34	1.84	11.3%
	2021-Jun	22,729	67.7	0.90	0.14	20.44	3.24	15.8%
	2021-Jul	23,255	72.2	1.26	0.20	29.25	4.70	16.1%
	2021-Aug	23,872	72.8	1.36	0.16	32.37	3.73	11.5%
	2021-Sep	24,511	70.5	1.31	0.11	32.11	2.66	8.3%
Off-peak (6AM-4PM and 10PM-12AM)	2020-Oct	18,556	69.7	0.46	-0.04	8.48	-0.73	-8.6%
	2020-Nov	18,911	62.4	0.55	0.06	10.37	1.12	10.8%
	2020-Dec	19,349	59.1	0.69	0.04	13.40	0.73	5.4%
	2021-Jan	19,879	58.1	0.59	0.03	11.71	0.55	4.7%
	2021-Feb	20,651	59.0	0.36	0.03	7.36	0.69	9.3%
	2021-Mar	20,948	58.2	0.31	0.02	6.44	0.32	5.0%
	2021-Apr	21,582	63.1	0.21	0.01	4.47	0.20	4.5%
	2021-May	22,110	64.1	0.28	0.03	6.15	0.59	9.6%
	2021-Jun	22,729	68.4	0.38	0.05	8.74	1.20	13.8%
	2021-Jul	23,255	73.1	0.67	0.08	15.49	1.97	12.7%
	2021-Aug	23,872	73.6	0.74	0.05	17.77	1.20	6.7%
	2021-Sep	24,511	71.8	0.70	0.05	17.22	1.24	7.2%
Super off-peak (12-6AM)	2020-Oct	18,556	60.6	0.91	-0.62	16.87	-11.42	-67.7%
	2020-Nov	18,911	51.0	1.01	-0.48	19.12	-9.02	-47.1%
	2020-Dec	19,349	47.8	1.06	-0.52	20.41	-10.00	-49.0%
	2021-Jan	19,879	48.2	1.06	-0.43	21.07	-8.45	-40.1%
	2021-Feb	20,651	48.6	1.03	-0.47	21.32	-9.74	-45.7%
	2021-Mar	20,948	49.1	1.05	-0.38	21.90	-7.94	-36.2%
	2021-Apr	21,582	55.2	0.95	-0.47	20.58	-10.20	-49.5%
	2021-May	22,110	58.5	0.99	-0.42	21.84	-9.30	-42.6%
	2021-Jun	22,729	61.5	1.05	-0.38	23.95	-8.60	-35.9%
	2021-Jul	23,255	66.4	1.19	-0.32	27.76	-7.48	-27.0%
	2021-Aug	23,872	66.4	1.18	-0.34	28.08	-8.05	-28.7%
	2021-Sep	24,511	64.8	1.14	-0.31	28.05	-7.52	-26.8%

[1] Participant weighted average temperature. SDG&E maps all customers to eight weather stations.

4.4 LOAD IMPACTS BY CUSTOMER TYPE

Figure 15 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. Customers with solar delivered large peak demand reduction due to the TOU rates than those without a solar installation. In addition, customers located in Northern San Diego County and Southern Orange County also delivered larger peak demand reductions than participants in other locations.

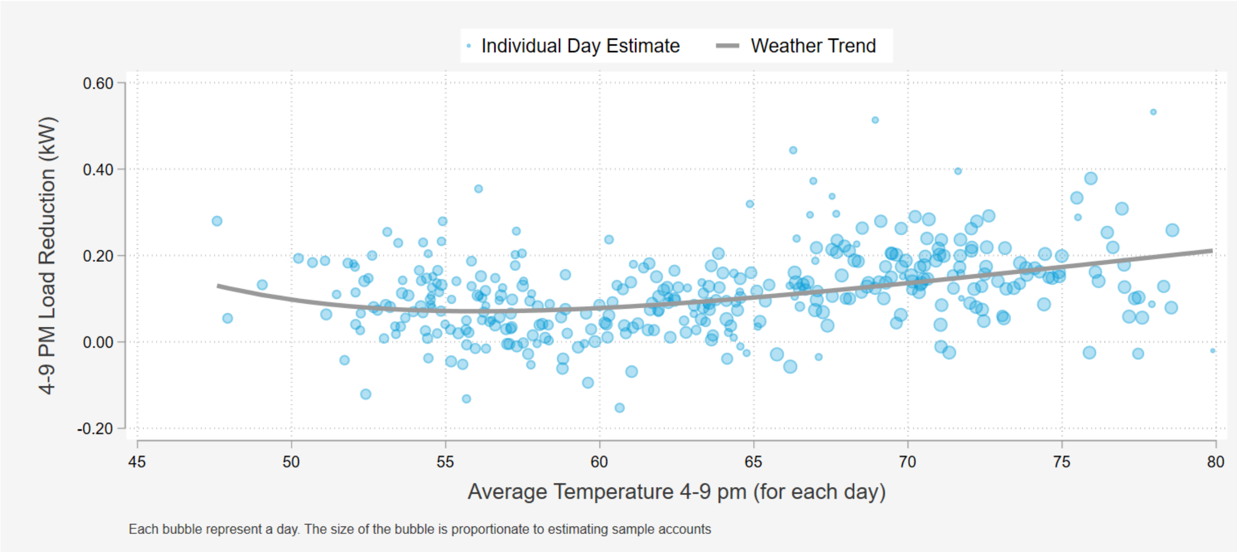
Figure 15: Load Impacts per Site for Key Customer Segments



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-offpeak 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 16 shows the relationship between the daily peak period (4-9) load impacts and weather for all 365 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.

Figure 16: Peak Period (4-9 PM) Load Impact Weather Sensitivity



4.6 KEY FINDINGS

- Most new enrollment is occurring on the EVTOU5 rate.
- 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 larger demand reductions on the highest system load days. On top 5 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 0.26 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 6 MW or demand reductions during those days.
- The peak demand reductions are generally larger when weather is hotter.
- Customers with rooftop solar and customer located in Northern San Diego County and Southern Orange County delivered higher than average demand reductions.

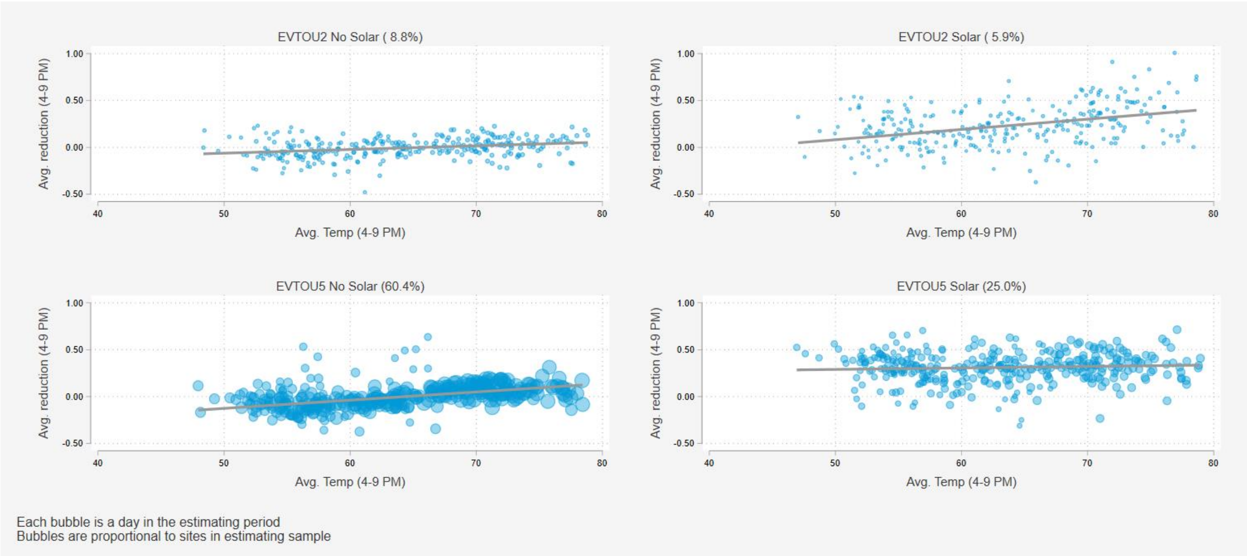
5 RESIDENTIAL EX-ANTE RESULTS

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 2020 to September 2021) 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 demand reductions and weather for 4 distinct segments – defined by the type of rate (EVTOU2 or EVTOU5) and the presence of rooftop solar. The granularity of the analysis was dictated by participant mix and the size of the estimating sample. Figure 17 shows the relationship between weather and demand reductions for each of the building blocks. Overall, there is a small correlation with weather, with larger demand reductions with hotter temperatures.

Figure 17: Impacts as a Function of Weather by Rate Type and Solar



Demand Side Analytics
DATA DRIVEN RESEARCH AND INSIGHTS

The pattern of reductions across events and segments was analyzed using a multi-variate regression model. 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.

5.2 OVERALL RESULTS

Figure 18 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. Table 7 shows the average ex-ante reduction per participant for May to October Impacts for the hours of 4-9 pm by daytype. The per customer reductions are shown under four different scenarios – SDG&E 1-in-2 and 1-in-10 weather conditions and CAISO 1-in-2 and 1-in-10 weather conditions. 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 18: Heatmap of Per Customer Ex-ante Load Reductions by Hour and Month

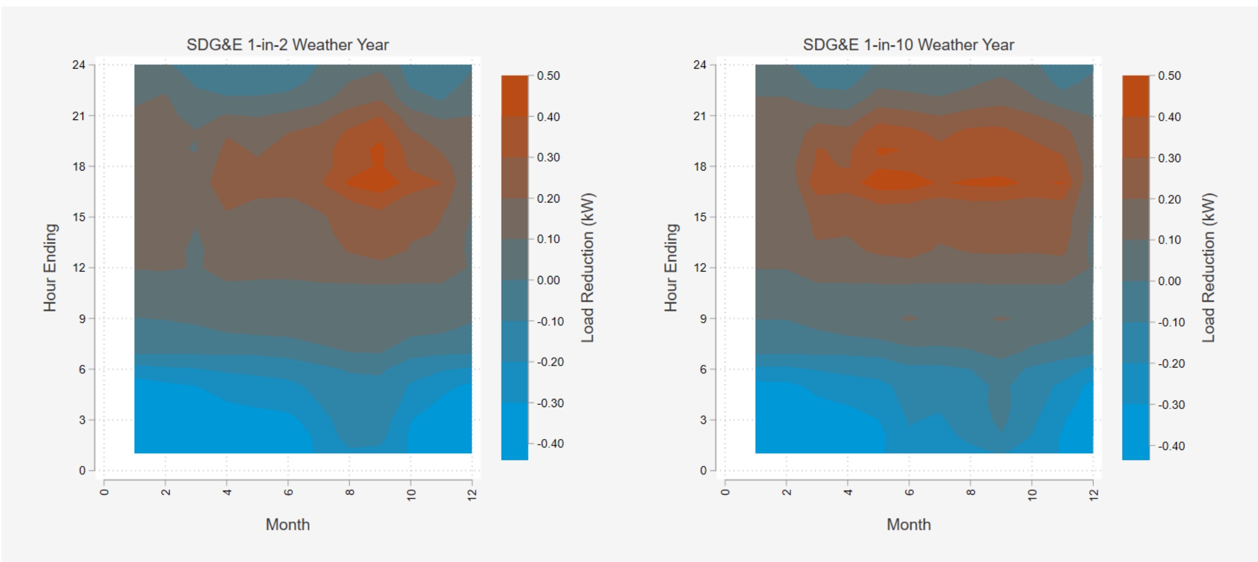


Table 7: Per Participant Peak Day Ex-ante Impacts (kW)

		SDG&E		CAISO	
Day Type	**Month**	**1-in-2**	**1-in-10**	**1-in-2**	**1-in-10**
AVERAGE WEEKDAY	05 May	0.14	0.15	0.14	0.17
	06 Jun	0.17	0.21	0.16	0.21
	07 Jul	0.24	0.25	0.22	0.26
	08 Aug	0.25	0.27	0.25	0.27
	09 Sep	0.24	0.28	0.24	0.28
	10 Oct	0.15	0.23	0.17	0.23
MONTHLY SYSTEM PEAK DAY	05 May	0.18	0.37	0.26	0.34
	06 Jun	0.21	0.36	0.22	0.34
	07 Jul	0.24	0.30	0.28	0.33
	08 Aug	0.34	0.34	0.32	0.37
	09 Sep	0.40	0.34	0.41	0.41
	10 Oct	0.25	0.31	0.31	0.38

Day Type	Month	SDG&E 1-in-2	SDG&E 1-in-10	CAISO 1-in-2	CAISO 1-in-10
TYPICAL EVENT DAY	08 Aug	0.30	0.34	0.31	0.36

Table 8 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 8: Aggregate August Monthly System Peak Day Demand Reduction Forecast (MW)

Forecast Year	Enrollment Forecast	SDG&E Weather 1-in-2	SDG&E Weather 1-in-10	CAISO Weather 1-in-2	CAISO Weather 1-in-10
2021	23,402	8.1	8.2	7.9	8.9
2022	33,050	11.1	11.2	10.7	12.2
2023	40,952	13.7	13.9	13.3	15.1
2024	48,415	16.2	16.5	15.7	17.9
2025	55,680	18.7	18.9	18.1	20.5
2026	61,181	20.5	20.8	19.9	22.6
2027	66,591	22.3	22.7	21.6	24.6
2028	71,982	24.1	24.5	23.4	26.6
2029	77,350	25.9	26.3	25.1	28.5
2030	82,861	27.8	28.2	26.9	30.6
2031	88,765	29.8	30.2	28.8	32.8
2032	95,089	31.9	32.4	30.9	35.1

Figure 19 and 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 19 shows profiles under 1-in-2 weather conditions, and Figure 20 shows profiles for 1-in-10. Note that the forecast year shown is 2022. The confidence band for the average impact over the 4-9 pm window is narrower than for individual hours.

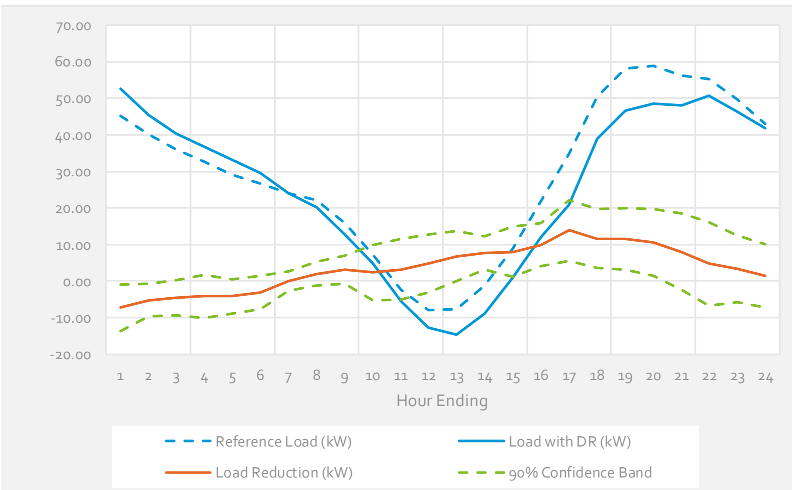
Figure 19: Aggregate Ex-ante Impact for 1-in-2 Weather Conditions, August Peak Day 2022

Table 1: Menu options

Type of Result	Aggregate Total
System (CAISO/SDG&E)	SDG&E
Weather Year	1-IN-2
Forecast Year	2022
Category	All
Subcategory	All
Day type	MONTHLY SYSTEM PEAK DAY
Month	08 Aug

Table 2: Event day information

Total sites	33,050
Daily Max Temp	88.8
Peak Period (4pm-9pm) Impact (MW)	11.08
Peak Period (4pm-9pm) Impact (%)	21.5%



Hour Ending	Reference Load (kW)	Load with DR (kW)	Load Reduction (kW)	% Load Reduction	Avg Temp (°F, Site-Weighted)	Uncertainty Adjusted 5th	Uncertainty Adjusted 95th	Standard Error	T-Statistic
1	45.24	52.55	-7.31	-16.2%	74.3	-13.75	-0.87	3.91	-1.87
2	40.20	45.42	-5.22	-13.0%	73.5	-9.68	-0.76	2.71	-1.93
3	35.93	40.45	-4.52	-12.6%	72.7	-9.28	0.23	2.89	-1.57
4	32.59	36.79	-4.19	-12.9%	72.1	-10.15	1.76	3.62	-1.16
5	29.00	33.21	-4.21	-14.5%	71.7	-8.85	0.43	2.82	-1.49
6	26.52	29.58	-3.05	-11.5%	71.4	-7.63	1.53	2.78	-1.10
7	24.09	24.12	-0.03	-0.1%	71.0	-2.68	2.62	1.61	-0.02
8	22.11	20.13	1.98	9.0%	72.7	-1.33	5.29	2.01	0.99
9	15.83	12.67	3.16	20.0%	76.1	-0.70	7.01	2.34	1.35
10	7.12	4.75	2.37	33.2%	80.8	-5.18	9.92	4.59	0.52
11	-2.31	-5.52	3.21	-138.9%	84.7	-5.01	11.43	5.00	0.64
12	-8.05	-12.84	4.79	-59.4%	87.0	-3.07	12.65	4.78	1.00
13	-7.77	-14.58	6.81	-87.6%	88.2	-0.07	13.69	4.19	1.63
14	-1.16	-8.84	7.68	-659.3%	88.7	3.10	12.26	2.78	2.76
15	8.87	0.87	7.99	90.1%	88.8	1.11	14.88	4.19	1.91
16	21.95	12.01	9.94	45.3%	88.6	4.06	15.82	3.58	2.78
17	34.80	20.98	13.83	39.7%	87.5	5.57	22.09	5.02	2.75
18	50.41	38.79	11.62	23.0%	86.0	3.64	19.59	4.85	2.40
19	57.99	46.52	11.47	19.8%	83.0	3.01	19.94	5.15	2.23
20	58.86	48.40	10.47	17.8%	81.0	1.37	19.57	5.53	1.89
21	56.12	48.09	8.02	14.3%	78.2	-2.43	18.47	6.35	1.26
22	55.30	50.60	4.70	8.5%	76.6	-6.68	16.07	6.91	0.68
23	49.60	46.28	3.32	6.7%	75.8	-5.90	12.53	5.60	0.59
24	43.09	41.70	1.39	3.2%	74.5	-7.30	10.08	5.28	0.26
Daily	Reference Load (kW)	Load with DR (kW)	Load Reduction (kW)	% Change	Avg Temp (°F, Site-Weighted)	Uncertainty Adjusted Impact -		Std Err	T-statistic
	kWh	kWh	kWh		F	5th	95th		
Overall	696.33	612.13	84.20	12.1%	79.4	77.08	91.32	4.33	19.45
Peak Hours Avg.	51.64	40.55	11.08	21.5%	83.1	9.30	12.86	1.08	10.25

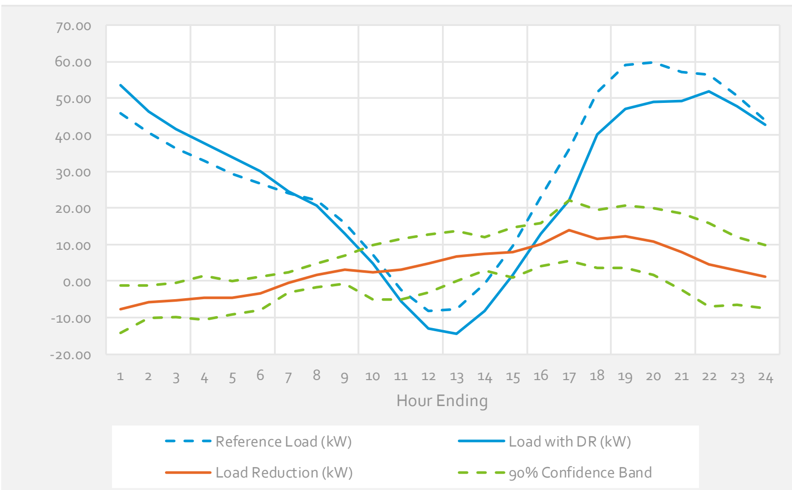
Figure 20: Aggregate Ex-ante Impact for 1-in-10 Weather Conditions, August Peak Day 2022

Table 1: Menu options

Type of Result	Aggregate Total
System (CAISO/SDG&E)	SDG&E
Weather Year	1-IN-10
Forecast Year	2022
Category	All
Subcategory	All
Day type	MONTHLY SYSTEM PEAK DAY
Month	08 Aug

Table 2: Event day information

Total sites	33,050
Daily Max Temp	88.9
Peak Period (4pm-9pm) Impact (MW)	11.25
Peak Period (4pm-9pm) Impact (%)	21.3%



Hour Ending	Reference Load (kW)	Load with DR (kW)	Load Reduction (kW)	% Load Reduction	Avg Temp (°F, Site-Weighted)	Uncertainty Adjusted		Standard Error	T-Statistic
						5th	95th		
1	45.90	53.64	-7.74	-16.9%	72.9	-14.18	-1.31	3.91	-1.98
2	40.53	46.27	-5.74	-14.2%	72.7	-10.20	-1.29	2.71	-2.12
3	36.22	41.45	-5.23	-14.5%	71.6	-9.99	-0.48	2.89	-1.81
4	32.94	37.59	-4.65	-14.1%	71.1	-10.61	1.30	3.62	-1.28
5	29.23	33.80	-4.58	-15.7%	70.7	-9.22	0.06	2.82	-1.62
6	26.64	29.97	-3.32	-12.5%	70.3	-7.90	1.26	2.78	-1.19
7	24.09	24.47	-0.38	-1.6%	69.7	-3.03	2.27	1.61	-0.24
8	22.17	20.60	1.56	7.1%	70.3	-1.74	4.87	2.01	0.78
9	15.88	12.84	3.04	19.1%	74.9	-0.82	6.90	2.34	1.30
10	7.18	4.80	2.38	33.2%	79.6	-5.17	9.93	4.59	0.52
11	-2.30	-5.51	3.21	-139.4%	83.9	-5.01	11.42	5.00	0.64
12	-8.09	-12.88	4.79	-59.2%	87.0	-3.07	12.65	4.78	1.00
13	-7.67	-14.50	6.82	-88.9%	88.2	-0.06	13.71	4.19	1.63
14	-0.73	-8.21	7.48	-1031.1%	87.7	2.90	12.06	2.78	2.69
15	9.58	1.75	7.83	81.8%	87.9	0.95	14.72	4.19	1.87
16	22.98	12.97	10.01	43.6%	88.9	4.13	15.89	3.58	2.80
17	35.93	22.11	13.82	38.5%	87.5	5.56	22.08	5.02	2.75
18	51.69	40.13	11.56	22.4%	85.8	3.58	19.54	4.85	2.38
19	59.12	46.96	12.16	20.6%	84.8	3.70	20.63	5.15	2.36
20	59.84	49.09	10.75	18.0%	81.8	1.65	19.85	5.53	1.94
21	57.04	49.11	7.93	13.9%	78.0	-2.52	18.38	6.35	1.25
22	56.38	51.94	4.43	7.9%	75.9	-6.94	15.81	6.91	0.64
23	50.63	47.88	2.75	5.4%	74.4	-6.46	11.96	5.60	0.49
24	43.83	42.70	1.14	2.6%	73.6	-7.55	9.83	5.28	0.22

Daily	Reference Load (kW)	Load with DR (kW)	Load Reduction (kW)	% Change	Avg Temp (°F, Site-Weighted)	Uncertainty Adjusted Impact -		Std Err	T-statistic
	kWh	kWh	kWh		F	5th	95th		
Overall	709.00	628.98	80.02	11.3%	78.7	72.90	87.14	4.33	18.49
Peak Hours Avg.	52.72	41.48	11.25	21.3%	83.6	9.47	13.02	1.08	10.40

5.3 COMPARISON TO PRIOR YEAR

Table 9 shows a comparison of vintage year 2020 and 2021 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. In terms of magnitude and direction, both vintages showed larger impacts in the critical summer months of June, July, and August. Overall, the 2021 per customer value are lower. The differences can be attributed to a few factors. The estimates were produced using different sets of customers: the vintage 2020 impacts were based on incremental sites in 2020 while the vintage 2021 impacts are based on incremental sites in 2021. The 2021 evaluation had more EVTOU5 incremental enrollment, fewer transitions from EVTOU2 to EVTOU5, and fewer EVTOU2 enrollments. There was also a fundamental shift in methods. The 2021 evaluation screened out sites that adopted electric vehicles, solar, or battery storage over the study period or the pre-treatment year to avoid mixing the effects of introduction of these non-routine events with the effect of the TOU rates. In addition, we employed a two stage matching process. In the first stage, electric vehicle propensities were estimated based on smart meter load patterns, but without a focus on load shapes or consumption (since both are affected by TOU rates). This allowed us to identify control candidates that had electric vehicles over the study period and pre-intervention year and match them to customers with electric vehicles that enrolled on EVTOU5 or EVTOU2.

Table 9: Comparison of Per Participant Ex-ante Demand Reductions under SDG&E Weather Scenarios (kW)

	Vintage Year 2020				Vintage Year 2021			
	EVTOU5		EVTOU2		EVTOU5		EVTOU2	
	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	0.25	0.25	0.04	0.04	0.18	0.35	0.18	0.42
June	0.33	0.40	0.12	0.15	0.21	0.34	0.21	0.40
July	0.40	0.43	0.15	0.16	0.23	0.29	0.25	0.33
August	0.43	0.44	0.15	0.15	0.32	0.32	0.38	0.38
September	0.50	0.52	0.17	0.18	0.38	0.33	0.46	0.39
October	0.37	0.38	0.13	0.13	0.24	0.29	0.26	0.34

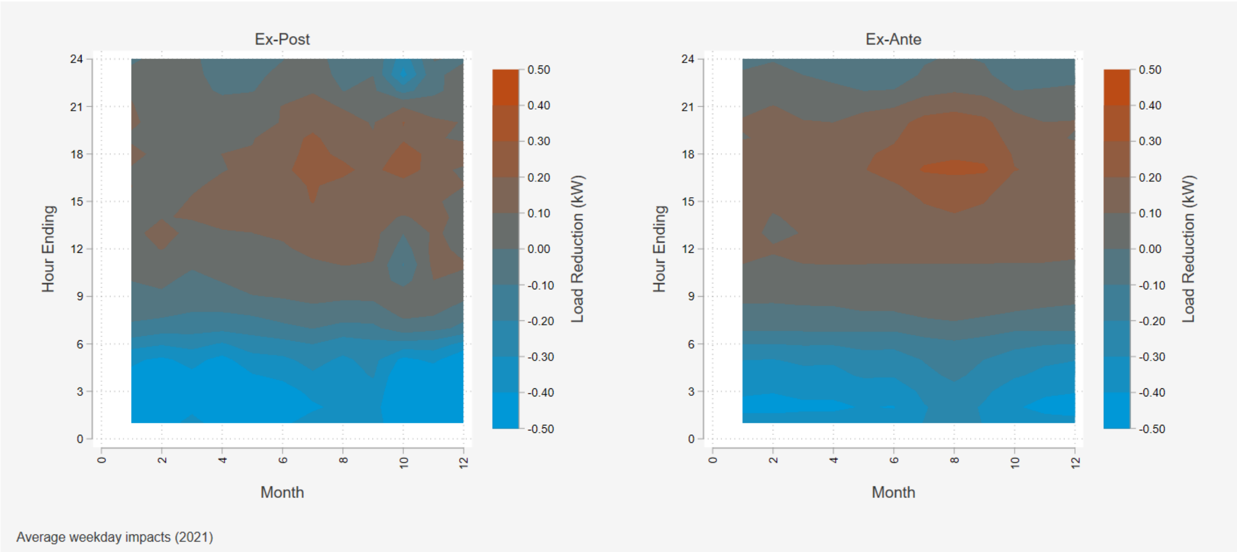
*Per Customer monthly system peak day reductions for 2022

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.

Figure 21 compares the per site ex-post load impacts to the ex-ante load impacts for the average weekday by month and hour. In magnitude, the ex-post load impacts are very similar 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. In addition, 2021 was relatively cool year compared to historical conditions.

Figure 21: Comparison of Ex-Post and Ex-Ante Per Customer Impacts under SDG&E peak conditions (2021)

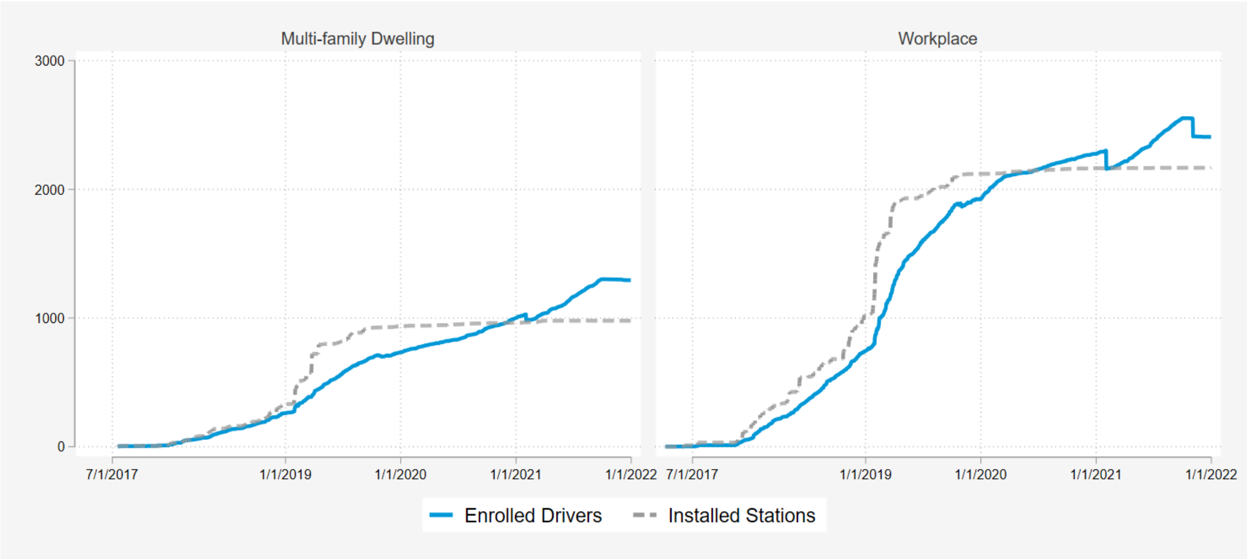


6 POWER YOUR DRIVE EVALUATION

This section focuses on the magnitude of demand reductions delivered by PYD participants for the time frame from January 1, 2019 through September 30, 2021. Through it's unique pricing structure, the Power Your Drive program encourages customers to shift their use from higher priced periods to lower cost periods, but do not directly control the charging behavior or customers or vehicles.

Since mid-2017 there has been a steady increase in PYD enrollments, reaching over 3,600 drivers actively enrolled by the end of 2021. SDG&E has 31,000 full battery electric vehicles, and 19,000 plug-in hybrid vehicles in its territory. Figure 22 below shows the PYD driver enrollment trends compared to station install rates from July 2017 through December 2021. There was a significant ramp-up effort in Station installs from July 2017 until January 2020. Initially, this install pace out-performed driver enrollment, and at times, more PYD stations were installed than drivers enrolled. In January 2020, station installs began to plateau while driver enrollment continued to increase, so driver enrollment has now exceeded the number of stations installed. Most drivers enrolled in the PYD program are residential EV owners.

Figure 22: Enrollment Trends vs. Station Install Rates for Multi-Family Dwellings and Workplaces

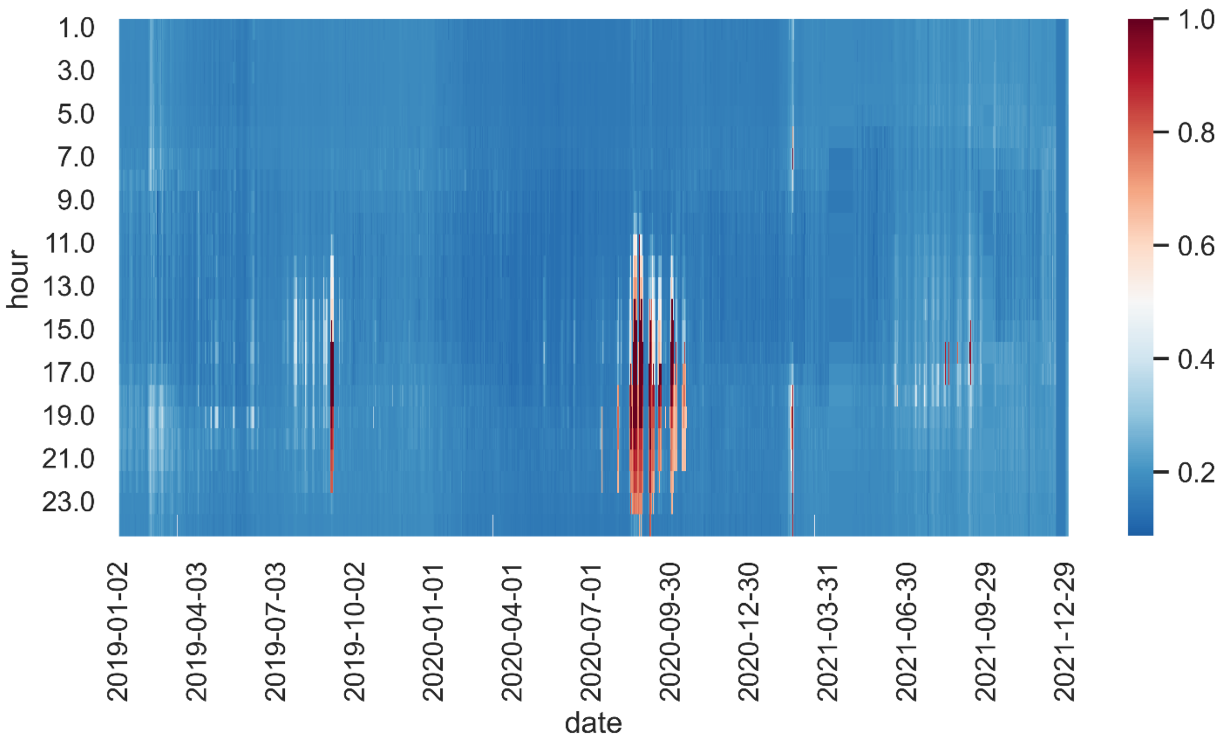


All chargers installed through the PYD program are billed on SDG&E's Vehicle-Grid Integration electric rate. The unique billing scheme for the PYD program is designed to encourage drivers to charge when there is abundant capacity on the grid. In particular, the Commodity Critical Peak Pricing (C-CPP) 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 Power Your Drive prices for the average location by hour and date. A large amount of high price days occurred in 2020 when California experienced resource shortages while high prices were rarely reached in 2021.

Table 10: SDG&E's Vehicle-Grid Integration Rate Components

Cost Component	Applies to
Base Rate	Charged on a per kWh basis and includes Transmission charges.
Commodity Rate	Charged on a per kWh basis and is based in the CAISO day-ahead and day-of hourly pricing. A Commodity Critical Peak Pricing (C-CPP) Hourly adder is added to the top 150 system peak hours on the CAISO day-ahead market.
Distribution Rate	Charged on a per kWh basis and includes a distribution base rate. Additionally, a VGI Distribution Critical Peak Pricing (D-CPP) Hourly Adder is added to the top 200 hours of the circuit when forecasted load exceeds the established threshold.

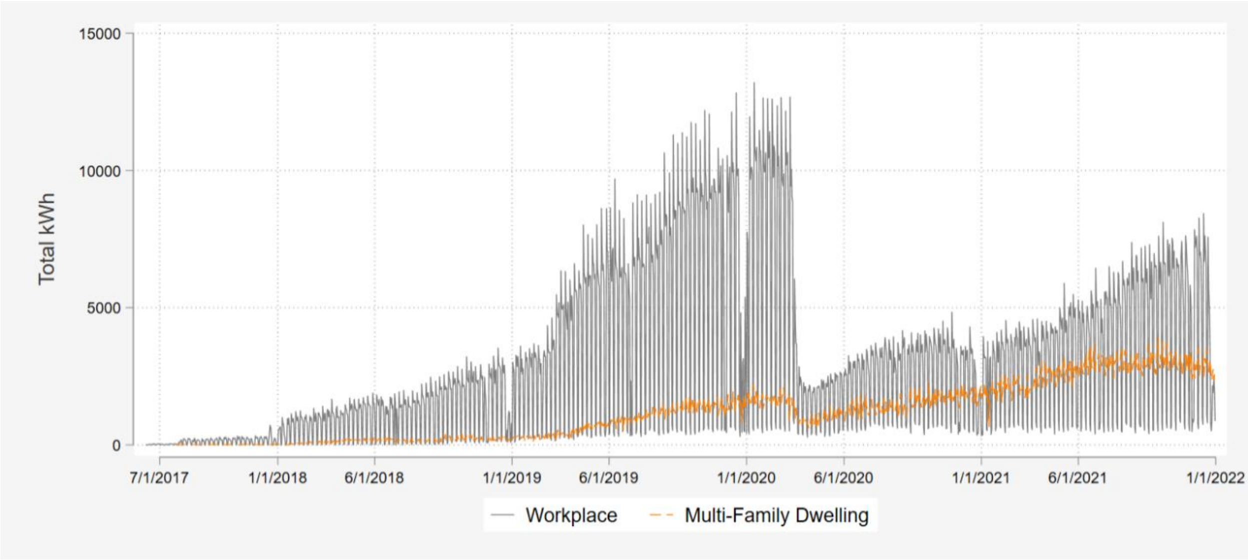
Figure 23: Heat map of Power Your Drive Prices by Date and Hour



6.1 COVID-19 IMPACTS ON CHARGING PATTERNS

As discussed in the Introduction, COVID-19 had a strong impact on the charging patterns of PYD participants at both the Workplace sites and Multi-Unit Dwellings. Figure 24 shows the total daily consumption of charging sessions by Site type. Both Workplace and Multi-Unit Dwellings charging sites saw a decrease in EV charging in March 2020. Since then, Multi-Unit Dwelling Sites have rebounded and surpassed pre-pandemic charging, while Workplaces are still climbing back towards pre-pandemic levels.

Figure 24: PYD Charging Trends by Site Type



6.2 EVALUATION FINDINGS

Multiple estimation methods were tested to optimize model performance. In the analysis we looked at the relationship between price and consumption patterns as well as "event" hour charging patterns versus non-event hour charging patterns. Events were defined as time periods when the system and circuit adders were in effect. These two methods are looking at two distinctly different relationships. The evaluation team estimated the impacts using panel regressions with multi-level fixed effects to control for customer effect, time effects (date and hour), and day of week effects.

Table 11: Fixed Effects Model Categories

Model	Site Type	Billing Type
Event	Workplace	Rate to Driver
Event	Workplace	Rate to Host
Event	Multi-Unit Dwellings	Rate to Driver
Price	Workplace	Rate to Driver
Price	Workplace	Rate to Host
Price	Multi-Unit Dwellings	Rate to Driver

6.3 PRICE SENSITIVITY

Figure 25 shows average hourly consumption patterns by average daily price bins at Workplace charging sites with Rate to Driver billing. To create the bins the average price per kWh for each day was calculated and binned at 10 cent intervals. In both 2019 and 2020 there is a clear drop in charging during high price days. In the summer of 2021, vaccinations were being administered and more people were heading back to the office. We can see almost a full return to pre-pandemic charging levels, but the effect of the pricing is likely confounded with the recovery from the pandemic, absent energy modeling. In specific, time period later in the year, had higher consumption level regardless of the prices in place. In addition, 2021 was a much more mild summer than 2020, and prices weren't as high, on average, for customers on this rate than in earlier years.

Figure 25: Average Consumption by Average Price Bin at Workplace sites with Rate to Driver billing

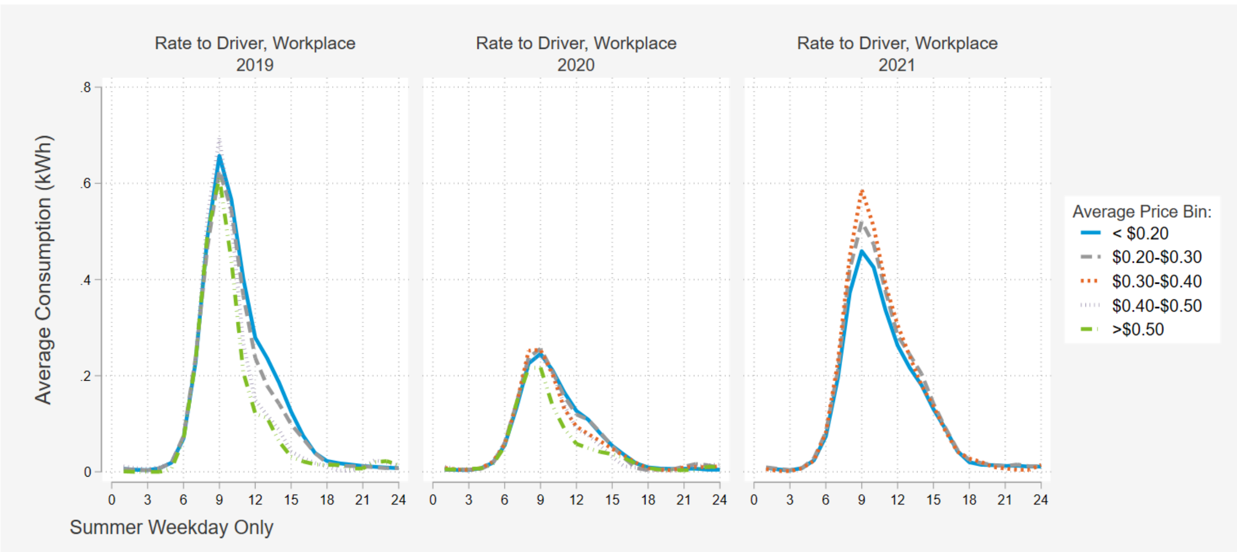


Figure 26 shows average charging consumption at Multi-Unit Dwellings by average price bin. In summer 2020, there appears to be a strong response to high price days, while again in 2021 we are see a mixed result due in part to the changes in driving and charging patterns as travel increased and social distancing decreased. The highest average price bin in summer 2021 is $0.30-$0.40, so average prices during 2021 summer were much lower than in 2020.

Figure 26: Average Consumption by Average Price Bin at Multi-Unit Dwellings with Rate to Driver billing

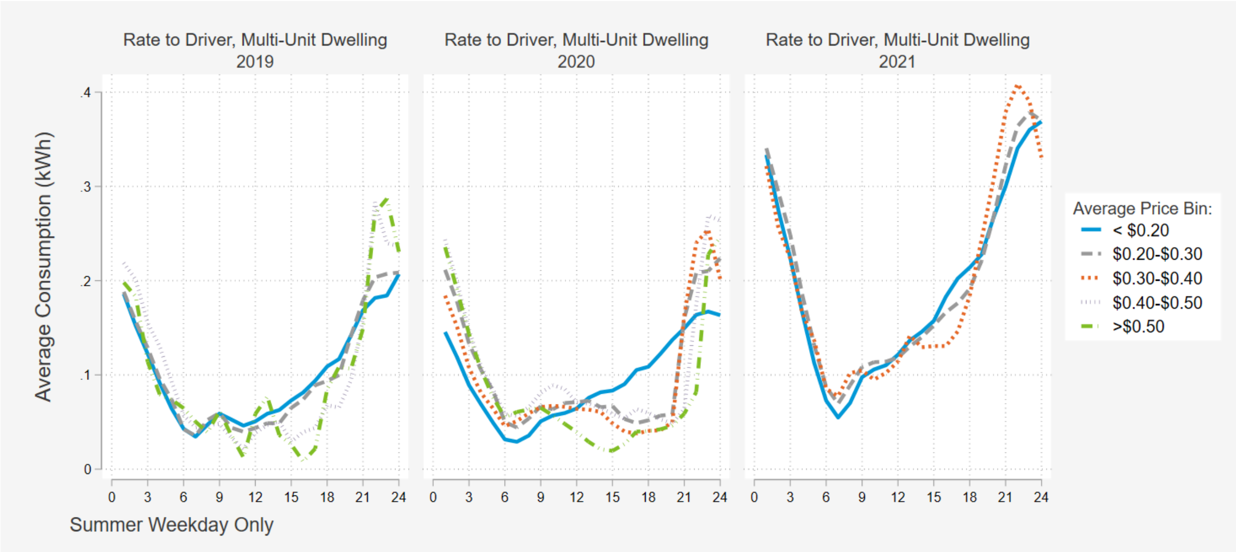


Figure 27 shows the average charging at workplace for rate to host billing. On the rate to host billing design, there is not evident response to higher prices. In fact, in the summer of 2020 there appears to be an increase in charging during high-price hours, as drives took advantage of free charging provided by workplaces when prices were high.

Figure 27: Average Charging by Average Price Bin at Workplace Sites with Rate to Host Billing

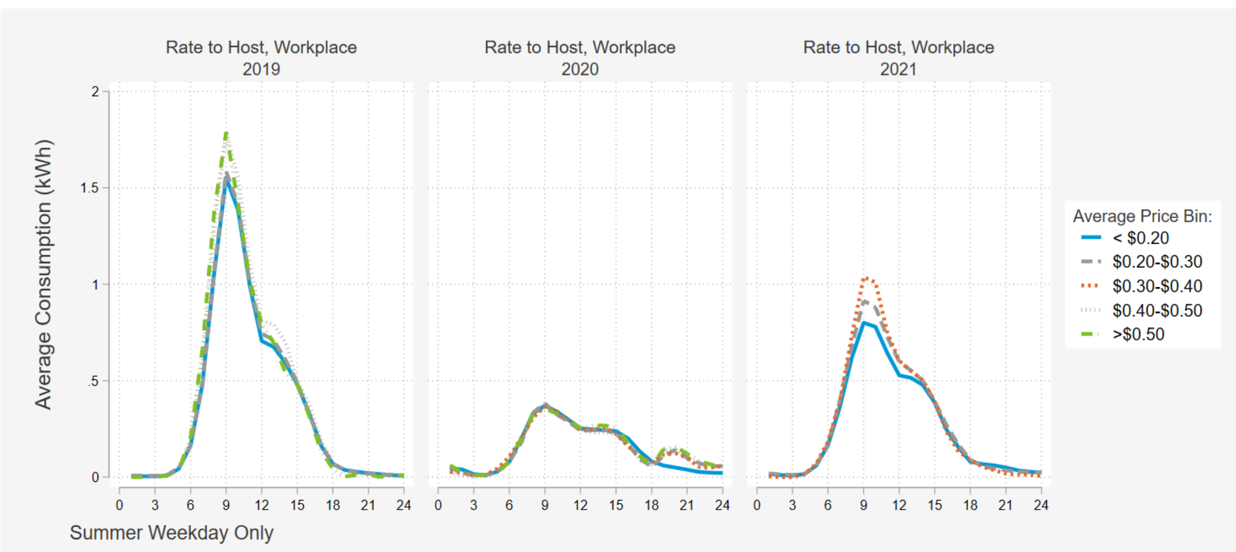


Figure 28 shows the relationship between price and average consumption. For Multi-Family Dwelling Rate-to-driver charging sites, drivers appear to respond to pricing by increasing consumption at lower prices and decreasing charging as prices increase. The same pattern can be observed at Workplace Rate to Driver charging sites. However, the opposite pattern is observed at Workplace Rate to Host charging sites. Charging appears to increase with increasing 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 28: Price vs Average Charging Consumption by Site Type and Billing

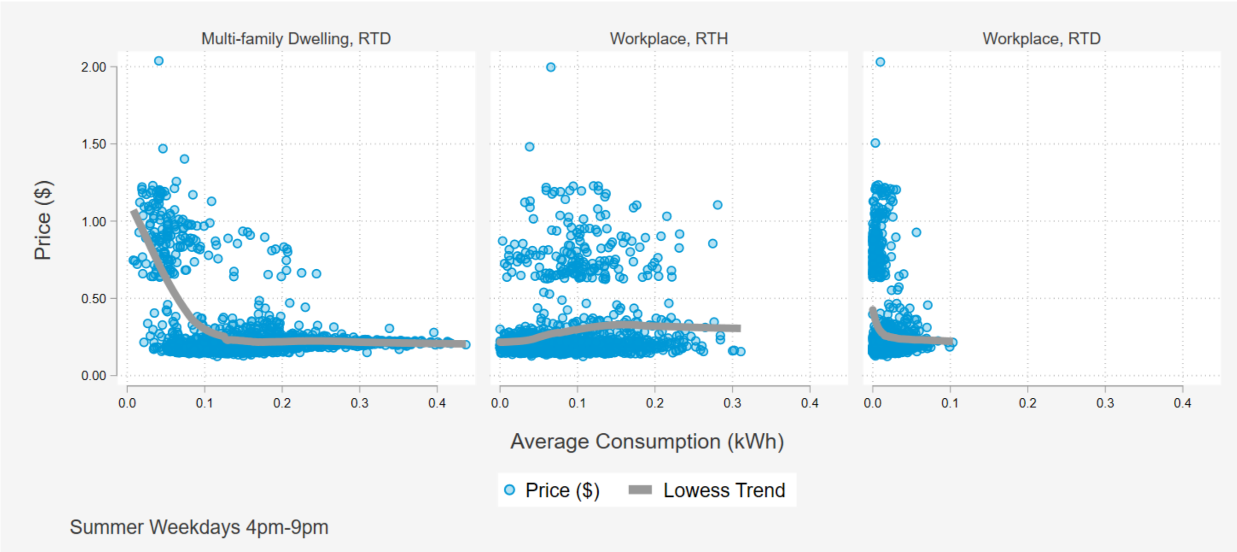


Table 12 covers the price model specifications. This model looks at the relationship between charging consumption trends and hour to hour changes in pricing.

Table 12: Price Response Regression Specifications

Category	Term	Description
Dependent Variable	ln_kWh[1]	Electricity delivered in kW for customer i, in hour h
Price	ln_price	Natural log of hourly price
	ln_price##Covid	Natural log of the price interacted with COVID19 indicator to capture charging respose changes as a result of COVID19
Fixed Effects	Station ID	Idividual Charging Station ID
	Date	Date Variable
	dow	Day of week indicator variables
	hour	Hour of Day indicator variables
Cluster	Date	Date Variable
	Station ID	Individual Charging Station ID

[1] 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.

Results in Figure 29 for Workplace Sites with Rate to Driver billing indicate that drivers decrease their charging by -0.024% for each 1% change in prices. For example, an increase in price from $0.20 to $0.60kW (200% increase) leads to a 5% decrease in demand. When interacted with the COVID19 time flag, we see that price response is no longer statistically significant over the covid time period.

Figure 29: Price Based Regression Results, Workplace Sites with Rate to Driver Billing

```
HDFE Linear regression                                Number of obs   = 19,978,003
Absorbing 4 HDFE groups                               F(   2,    1003) =      43.82
Statistics robust to heteroskedasticity               Prob > F        =     0.0000
                                                      R-squared       =     0.0637
                                                      Adj R-squared   =     0.0636
Number of clusters (date)       =      1,004          Within R-sq.    =     0.0002
Number of clusters (station_id) =      1,163          Root MSE        =     0.2143

                          (Std. Err. adjusted for 1,004 clusters in date station_id)
```

ln_kwh	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
ln_price	-.0237116	.0027817	-8.52	0.000	-.0291703	-.0182529
covid	0	8.87e-17	0.00	1.000	-1.74e-16	1.74e-16
c.ln_price#c.covid	.0349431	.0037722	9.26	0.000	.0275407	.0423454
_cons	.0269814	.0026225	10.29	0.000	.0218351	.0321276

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs	
date	1004	1004	0	*
station_id	1163	1163	0	*
hour	24	0	24	
dayofweek	7	1	6	

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

Results in Figure 30 for Workplace sites with rate to host billing indicate that customers tend to charge more when prices are higher. In other words, when prices are higher drivers take advantage of the "free" charging at work and charge more. COVID did not appear to affect charging behavior at workplaces with rate to host billing.

Figure 30: Price Based Regression Results, Workplace Sites with Rate to Host Billing

```
HDFE Linear regression                            Number of obs   = 12,679,224
Absorbing 4 HDFE groups                           F(   2,    768) =      66.10
Statistics robust to heteroskedasticity           Prob > F        =     0.0000
                                                  R-squared       =     0.1168
                                                  Adj R-squared   =     0.1167
Number of clusters (date)      =      1,004       Within R-sq.    =     0.0010
Number of clusters (station_id) =        769      Root MSE        =     0.3075

                         (Std. Err. adjusted for 769 clusters in date station_id)
```

ln_kwh	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
ln_price	.0396021	.0070718	5.60	0.000	.0257198	.0534844
covid	0	2.46e-10	0.00	1.000	-4.83e-10	4.83e-10
c.ln_price#c.covid	-.0003777	.0082661	-0.05	0.964	-.0166046	.0158491
_cons	.1359648	.0062074	21.90	0.000	.1237792	.1481503

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs	
date	1004	1004	0	*
station_id	769	769	0	*
hour	24	0	24	
dayofweek	7	1	6	

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

Figure 31 shows regression results for Multi-Unit Dwelling Sites with Rate to Driver Billing. We saw a decrease in average charging consumption by-0.022% for each 1% change in pricing. To illustrate a change in prices from $0.20/kWh to $0.60/kWh (a 200% increase) leads to reduction in charging of 4.4%. At Multi-Unit Dwellings, the COVID interaction did not have a statistically significant response, meaning that pre-and post-pandemic response to prices was similar.

Figure 31: Price Based Regression Results, Multi-Unit Dwelling Sites with Rate to Driver Billing

```
HDFE Linear regression                            Number of obs   = 12,904,476
Absorbing 4 HDFE groups                           F(   2,     835) =     101.11
Statistics robust to heteroskedasticity           Prob > F        =     0.0000
                                                  R-squared       =     0.0343
                                                  Adj R-squared   =     0.0341
Number of clusters (date)      =      1,004       Within R-sq.    =     0.0002
Number of clusters (station_id) =        836      Root MSE        =     0.2667

                      (Std. Err. adjusted for 836 clusters in date station_id)
------------------------------------------------------------------------------
                 |               Robust
          ln_kwh |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
        ln_price |  -.0222378   .0041112    -5.41   0.000    -.0303072   -.0141684
           covid |          0   9.97e-19     0.00   1.000    -1.96e-18    1.96e-18
                 |
c.ln_price#c.covid |   .0033132   .0040221     0.82   0.410    -.0045814    .0112077
                 |
           _cons |   .0106222   .0031061     3.42   0.001     .0045256    .0167189
------------------------------------------------------------------------------

Absorbed degrees of freedom:
-----------------------------------------------------+
 Absorbed FE | Categories  - Redundant  = Num. Coefs |
-------------+---------------------------------------|
        date |      1004        1004           0    *|
  station_id |       836         836           0    *|
        hour |        24           0          24     |
   dayofweek |         7           1           6     |
-----------------------------------------------------+
* = FE nested within cluster; treated as redundant for DoF computation
```

6.4 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. The sections below cover results from the event-based regressions.

Table 13: 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
	event##covid	Event hour indicator interacted with COVID19 indicator to capture charging response changes as a result of COVID19
Fixed Effects	Station ID	Idividual Charging Station ID
	Date	Date Variable
	dow	Day of week indicator variables
	hour	Hour of Day indicator variables
Cluster	Date	Date Variable
	Station ID	Individual Charging Station ID

Figure 32 shows the results of the event based regression for Workplace charging sites on the Rate to Driver billing. The coefficient on the event variable for this model is -0.032. This tells us that the charging behavior of PYD participants at Workplace Sites decreases by 2.8% during event hours. The interaction between events and the COVID variable indicates an increase in customer charging during event hours by 3.3%. However, the price response and the price response interacted with COVID are not jointly significant. The main interpretation is that workplace charging behavior changed with COVID, likely because the mix of workers driving to offices and workplaces changed over the timeframe.

[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 32: Event Based Regression Results, Workplace Sites with Rate to Driver Billing

```
HDFE Linear regression                                Number of obs   = 19,978,003
Absorbing 4 HDFE groups                               F(   2,    1003) =     43.13
Statistics robust to heteroskedasticity               Prob > F        =    0.0000
                                                      R-squared       =    0.0636
                                                      Adj R-squared   =    0.0635
Number of clusters (date)     =      1,004            Within R-sq.    =    0.0001
Number of clusters (station_id) =      1,163          Root MSE        =    0.2143

                       (Std. Err. adjusted for 1,004 clusters in date station_id)
```

ln_kwh	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
event	-.0280865	.0031238	-8.99	0.000	-.0342165	-.0219565
covid	0	3.30e-19	0.00	1.000	-6.48e-19	6.48e-19
c.event#c.covid	.0330101	.0038265	8.63	0.000	.0255012	.040519
_cons	.0321433	.0000369	870.62	0.000	.0320709	.0322158

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs	
date	1004	1004	0	*
station_id	1163	1163	0	*
hour	24	0	24	
dayofweek	7	1	6	

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

Figure 33 shows the event based regression results for Workplace sites on rate to host billing. The rate to host billing type will apply billing associated with EV charging to the site host's electric bill. As expected, we don't see a response to event hours because drivers are not incentivized to stop charging when prices are high. In fact, we see an increase in charging by 6.98% during event hours as drivers take advantage of the "free" charging. When this variable is interacted with a COVID19 indicator, we saw a decrease in charging by 4.42% in post-COVID. That would still leave an increase in charging of 2.55% during event hours.

Figure 33: Event Based Regression Results for Workplace Sites with Rate to Host Billing

```
HDFE Linear regression                            Number of obs   = 12,731,009
Absorbing 4 HDFE groups                           F(   2,    777) =      45.63
Statistics robust to heteroskedasticity           Prob > F        =     0.0000
                                                  R-squared       =     0.1165
                                                  Adj R-squared   =     0.1164
Number of clusters (date)      =      1,004       Within R-sq.    =     0.0007
Number of clusters (station_id) =        778      Root MSE        =     0.3087

                     (Std. Err. adjusted for 778 clusters in date station_id)
```

ln_kwh	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
event	.0697819	.0103461	6.74	0.000	.0494722	.0900916
covid	0	2.35e-18	0.00	1.000	-4.60e-18	4.60e-18
c.event#c.covid	-.0442353	.0110894	-3.99	0.000	-.066004	-.0224667
_cons	.0665116	.0001944	342.22	0.000	.0661301	.0668931

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs	
date	1004	1004	0	*
station_id	778	778	0	*
hour	24	0	24	
dayofweek	7	1	6	

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

Figure 34 shows the results from the event-based regression for Multi-Unit Dwellings on Rate to Driver billing. The coefficient on the event variable for this model is -0.032. This tells us that the charging behavior of PYD participants at Multi-Unit dwellings decreases by 3.2% during event hours. The interaction between events and the COVID variable is not statistically significant, indicating that the price response at multi-family dwellings did not change with the COVID pandemic.

Figure 34: Event Based Regression Results for Multi-Unit Dwelling Sites with Rate to Driver billing

```
HDFE Linear regression                                 Number of obs   = 12,904,476
Absorbing 4 HDFE groups                                F(   2,    835) =      86.14
Statistics robust to heteroskedasticity                Prob > F        =     0.0000
                                                       R-squared       =     0.0342
                                                       Adj R-squared   =     0.0341
Number of clusters (date)      =      1,004            Within R-sq.    =     0.0002
Number of clusters (station_id) =       836            Root MSE        =     0.2667

                         (Std. Err. adjusted for 836 clusters in date station_id)
```

ln_kwh	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
event	-.0320222	.0066305	-4.83	0.000	-.0450367	-.0190078
covid	0	2.06e-19	0.00	1.000	-4.05e-19	4.05e-19
c.event#c.covid	.0038074	.0064321	0.59	0.554	-.0088176	.0164325
_cons	.0461197	.0000379	1217.59	0.000	.0460454	.046194

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs	
date	1004	1004	0	*
station_id	836	836	0	*
hour	24	0	24	
dayofweek	7	1	6	

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

6.5 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. However, they are not highly price sensitive.
- 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.
- The pandemic led to substantial change in commute and charging patterns. In specific, it affected the price responsiveness of workplace charging, likely because the mix of drivers going to the workplace also changed.

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 saturation 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 2.4M vehicles in SDG&E territory, and the grid implications of transportation electrification are large. It has become increasingly important to provide customers incentives and tools to manage charging to lower bills and reduce use during peak hours.

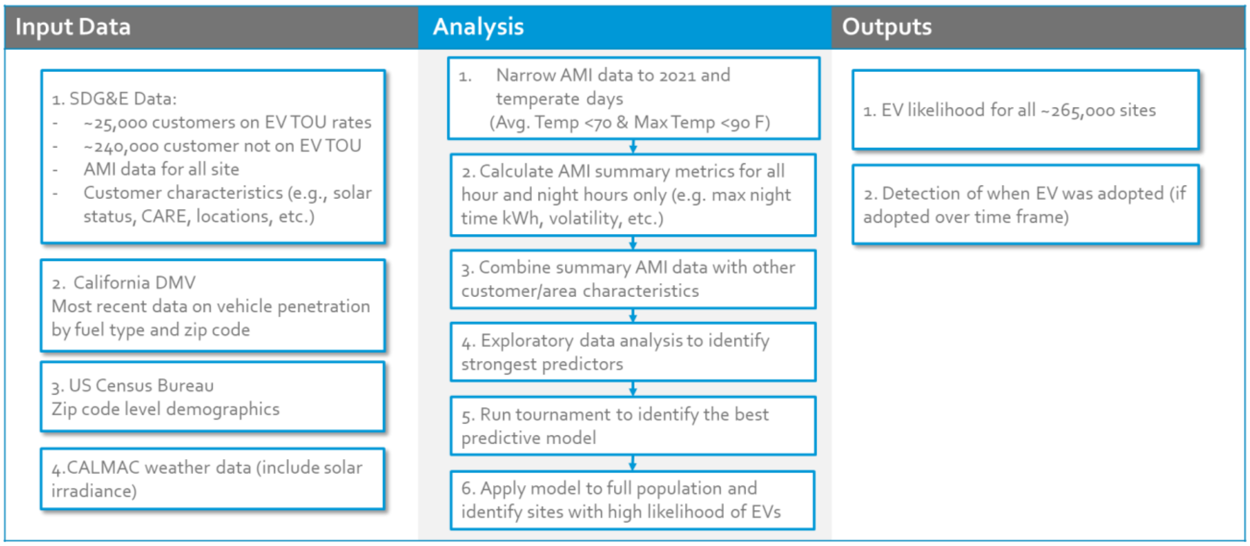
Key recommendations from the evaluation are:

- **Evaluate 1st year impacts for all sites that reached a full year of experience with electric vehicle time-of-use rates.** Currently, the evaluation includes all incremental sites that enrolled on the rate over the study period. As a result, the number of sites evaluated for October is small and grows during the study period. The approach creates two challenges. The sample size for early months is inherently small, and we have very little data on behavior with TOU rates for the most recent enrollments. Shifting from analyzing sites that enrolled over the study period 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 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.
- **Track historical first-year savings to avoid extrapolating from the new cohort of participants to the full population.** Currently, the evaluation extrapolates the impacts from the new cohort of participants to the full population. This is done because it is often not feasible to reliably estimate the TOU price response for sites that have been enrolled on the TOU rates for multiple years. The pre-TOU data is too distant in time for a reliable analysis. An alternative is to track first-year savings by enrollment cohort, enabling SDG&E to estimate the aggregate impacts better.

- **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.
- **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..

APPENDIX A: IDENTIFYING A CONTROL GROUP WITH ELECTRIC VEHICLES

A.1 Approach



1: Exploratory Data Analysis

- Use customers who are and are not on EV TOU rates (50/50 split – sample of 4,000)
- Explore relationship of all possible predictive variables (plots, bivariate regressions)
- Track metrics to identify the best predictors (Area under the curve and F1 score)
- For co-linear variables keep the best one

2: Model Tournament

- Define multiple models (13 models)
- Randomly assign to training/testing group (75/25)
- Train each model on predictive features
- Predict out of sample
- Record out of sample
- Repeat Steps 2-5 10X for each model

3: Apply best model

- Run final model on entire dataset
- Predict probability of EV ownership
- Finding matches for each EV site based on propensity score

A.2 Exploratory Data Analysis Bivariate Regression Results

Variable	AUC	F1	Precision	Recall / Sensitivity	Specificity	% Classified correctly (default 50%)
night_p98kwh	0.905	0.803	91.2%	71.7%	93.1%	82.4%
night_avgkwh	0.889	0.786	86.4%	72.1%	88.7%	80.4%
all_p98kwh	0.881	0.776	88.9%	68.8%	91.4%	80.1%
night_maxkwh	0.869	0.788	85.4%	73.3%	87.5%	80.4%
all_maxkwh	0.851	0.777	82.9%	73.0%	85.0%	79.0%
night_concentration	0.819	0.755	75.4%	75.6%	75.3%	75.4%
bins_pct_8to6am	0.808	0.746	83.9%	67.1%	87.1%	77.1%
night_concentration_p95	0.789	0.730	75.8%	70.4%	77.6%	74.0%

all_concentration	0.772	0.714	73.7%	69.2%	75.4%	72.3%
pct_8to6am	0.762	0.701	86.3%	59.1%	90.7%	74.9%
night_normsd	0.751	0.671	72.2%	62.6%	75.9%	69.3%
bins_all_avgkwh	0.728	0.640	72.0%	57.6%	77.6%	67.6%
all_normsd	0.686	0.623	76.5%	52.5%	83.9%	68.2%
all_avgkwh	0.676	0.641	70.8%	58.6%	75.8%	67.2%
all_avgkwh	0.676	0.641	70.8%	58.6%	75.8%	67.2%
all_concentration_p95	0.656	0.609	65.5%	56.9%	70.1%	63.5%
solar_kw	0.636	0.530	72.6%	41.7%	84.3%	63.0%
bins_solar_kw	0.636	0.534	72.6%	42.3%	84.0%	63.1%
solar	0.631	0.534	72.6%	42.3%	84.0%	63.1%
weather_station	0.630	0.510	68.5%	40.7%	81.4%	61.0%
zip3	0.623	0.423	77.0%	29.2%	91.3%	60.2%
zip4	0.619	0.446	65.0%	33.9%	83.5%	60.0%
pct_hybrid	0.613	0.600	60.8%	59.3%	61.9%	60.6%
all_loadfactor	0.590	0.568	56.1%	57.6%	54.9%	56.2%
night_loadfactor	0.572	0.498	55.6%	45.0%	64.1%	54.5%
bins_pct_new	0.559	0.502	56.7%	45.0%	65.7%	55.3%
pct_green	0.554	0.531	53.3%	52.9%	53.7%	53.3%
lowincome	0.542	0.671	52.4%	93.4%	15.1%	54.2%
night_percentileload	0.542	0.492	53.2%	45.8%	59.7%	52.8%
pct_bev	0.526	0.549	50.3%	60.3%	40.5%	50.4%
housingunits	0.525	0.495	53.4%	46.2%	59.8%	53.0%
pct_phev	0.524	0.510	52.4%	49.6%	54.9%	52.3%
percapitaincome	0.524	0.515	50.9%	52.2%	49.8%	51.0%
cca	0.523	0.661	51.3%	93.1%	11.6%	52.3%
medianyearstruturebuilt	0.517	0.513	50.3%	52.4%	48.3%	50.3%
climate_zone	0.516	0.581	51.1%	67.2%	35.7%	51.5%
battery_kw	0.515	0.074	82.8%	3.9%	99.2%	51.5%
bins_battery_kw	0.515	0.074	82.8%	3.9%	99.2%	51.5%
battery	0.515	0.074	82.8%	3.9%	99.2%	51.5%
newcars_total	0.515	0.489	50.1%	47.8%	52.4%	50.1%
pct_poverty	0.511	0.536	49.8%	58.1%	41.6%	49.8%
population	0.509	0.515	49.0%	54.2%	43.8%	49.0%
medianage	0.508	0.497	51.5%	48.1%	54.7%	51.4%
all_percentileload	0.507	0.452	49.9%	41.4%	58.4%	49.9%
pct_new	0.502	0.480	51.6%	45.0%	57.9%	51.4%
povertycount	0.501	0.425	53.3%	35.3%	69.1%	52.2%

A.3 EV Propensity Tournament Models and Results

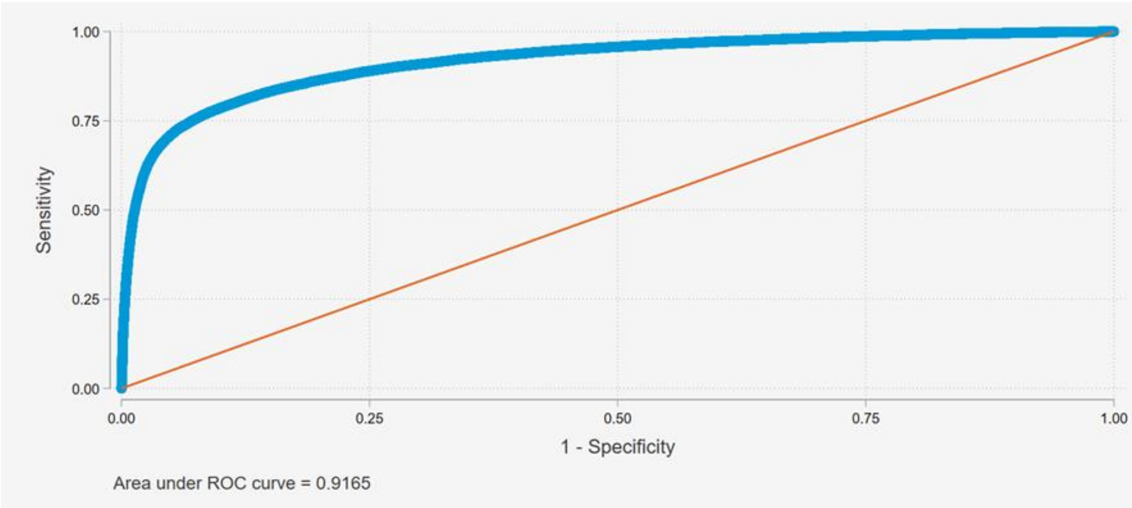
Model No.	AUC	F1	Precision	Recall / Sensitivity	Specificity	% Correctly Classified (default)
12	0.9172	0.8429	88.0%	80.9%	89.0%	84.9%
13	0.9170	0.8427	88.0%	80.9%	88.9%	84.9%
11	0.9168	0.8412	87.8%	80.8%	88.8%	84.8%
9	0.9159	0.8405	87.9%	80.5%	89.0%	84.7%

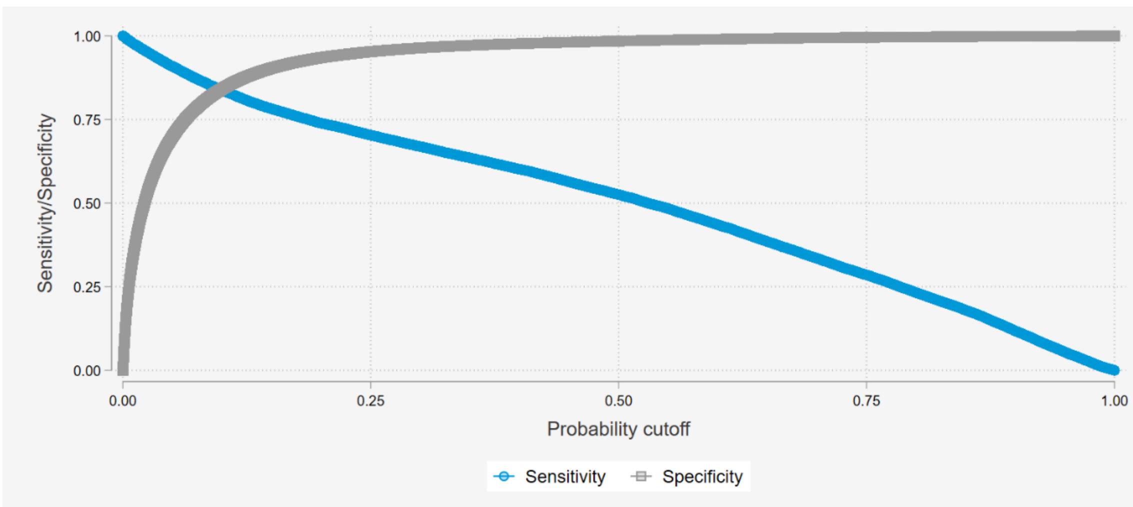
10	0.9159	0.8405	87.9%	80.5%	89.0%	84.7%
8	0.9156	0.8413	88.0%	80.6%	89.0%	84.8%
7	0.9154	0.8382	87.8%	80.2%	88.8%	84.5%
4	0.9047	0.8233	87.9%	77.5%	89.3%	83.4%
5	0.9047	0.8235	87.8%	77.5%	89.3%	83.4%
3	0.9047	0.8233	87.8%	77.5%	89.3%	83.4%
6	0.9039	0.8221	87.5%	77.5%	88.9%	83.2%
2	0.8985	0.8141	89.1%	74.9%	90.9%	82.9%
1	0.8935	0.8086	91.4%	72.5%	93.2%	82.8%

A.4 FINAL EV PROPESNITY MODEL

```
Logistic regression                             Number of obs     =    232,417
                                                LR chi2(30)       =   72237.82
                                                Prob > chi2       =     0.0000
Log likelihood =   -42900.6                     Pseudo R2         =     0.4571
```

evtou	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
night_p98kwh	1.326908	.0062446	60.10	0.000	1.314725	1.339203
night_concentration	31.66552	2.564162	42.67	0.000	27.01838	37.11196
night_normsd	2.061051	.0379112	39.32	0.000	1.98807	2.136711
bins_all_avgkwh						
2	.8873724	.0357459	-2.97	0.003	.820006	.9602731
3	1.400463	.0544795	8.66	0.000	1.297654	1.511417
4	2.675091	.0976299	26.96	0.000	2.490424	2.873452
5	4.997239	.1964166	40.93	0.000	4.626724	5.397425
bins_solar_kw						
4	2.693546	.1063638	25.09	0.000	2.49294	2.910294
6	2.763114	.107406	26.15	0.000	2.560421	2.981853
8	2.554295	.1130176	21.19	0.000	2.342118	2.785694
20	1.569079	.0755766	9.35	0.000	1.427729	1.724424
battery	1.480394	.0910729	6.38	0.000	1.312236	1.670101
all_concentration	2.383523	.1945494	10.64	0.000	2.03115	2.797027
all_loadfactor	.0987309	.0131312	-17.41	0.000	.0760752	.1281335
weather_station						
CARLSBAD	.7308863	.0414497	-5.53	0.000	.6539986	.8168133
GILLESPIE FIELD	2.329419	.1464675	13.45	0.000	2.059332	2.634928
LINDBERGH FIELD	1.514562	.0963482	6.53	0.000	1.337021	1.715678
MIRAMAR	.8904911	.0521827	-1.98	0.048	.7938697	.9988722
MONTGOMERY FIELD	1.292771	.0818785	4.05	0.000	1.141853	1.463636
OCEANSIDE	3.547989	.2270858	19.79	0.000	3.129695	4.022191
RAMONA	.8908635	.0572379	-1.80	0.072	.7854554	1.010417
SANTA ANA	4.94823	.3204294	24.69	0.000	4.35842	5.617856
bins_pct_new						
2	.7174005	.0250729	-9.50	0.000	.6699038	.7682647
3	1.377749	.0508602	8.68	0.000	1.281586	1.481128
4	1.298944	.0530515	6.40	0.000	1.199018	1.407198
5	1.186232	.0435428	4.65	0.000	1.103887	1.274719
pct_hybrid	1.18e-13	1.55e-13	-22.64	0.000	8.94e-15	1.55e-12
lowincome	.5376503	.0180681	-18.47	0.000	.5033785	.5742555
pct_poverty	.1849391	.0525435	-5.94	0.000	.1059722	.3227494
housingunits	1.000033	1.83e-06	17.90	0.000	1.000029	1.000036
_cons	.0020088	.0001815	-68.72	0.000	.0016827	.0023981





Sensitivity	Pr(+| D)	66.47%
Specificity	Pr(-|~D)	96.67%
Positive predictive value	Pr(D| +)	70.48%
Negative predictive value	Pr(~D| -)	96.01%
False + rate for true ~D	Pr(+|~D)	3.33%
False - rate for true D	Pr(-| D)	33.53%
False + rate for classified +	Pr(~D| +)	29.52%
False - rate for classified -	Pr(D| -)	3.99%
Correctly classified		93.44%