



Demand Side Analytics

DATA DRIVEN RESEARCH AND INSIGHTS

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2026 Load Impact Evaluation of San Diego Gas and Electric's Vehicle Grid Integration Rate



Prepared for San Diego Gas & Electric

By Demand Side Analytics, LLC

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Demand Side Analytics Team

- Marshall Blundell, Ph.D.
- David Pojunas, M.A.
- Josh Bode, M.P.P.

SDG&E Team

- Lizzette Garcia-Rodriguez
- Erich Kevari

ABSTRACT

This report summarizes the findings of San Diego Gas and Electric's (SDG&E) Vehicle Grid Integration (VGI) rate. In preparation for growth in electric vehicles (EVs) in its territory, SDG&E deployed an infrastructure program, Power Your Drive, focused on encouraging EV adoption by reducing barriers such as the expense and difficulty of installing charging equipment at multi-family dwellings (MUDs) and workplaces. EV charging at these sites is billed under SDG&E's VGI rate, a dynamic hourly rate that incorporates day-ahead hourly market prices, distribution cost recovery, and adders for the top 150 system load hours and top 200 distribution circuit load hours. For sites where drivers faced dynamic prices, we estimate a price elasticity of demand for charging of 0.34 at workplaces, and 0.28 at MUDs. We find little evidence of price sensitivity at sites where drivers do not pay for charging. On the top 5 load days for CAISO gross loads, sites curtailed demand during peak hours by 20.1% (3.6 MW) on average.

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1 EXECUTIVE SUMMARY

This report summarizes the evaluation findings for San Diego Gas and Electric's (SDG&E) Vehicle Grid Integration (VGI) rate. In preparation for growth in electric vehicles (EVs), SDG&E deployed the Power Your Drive (PYD) infrastructure program focused on encouraging EV adoption by reducing barriers such as the expense and difficulty of installing charging equipment at multi-family dwellings (MUDs) and workplaces. EV charging at these sites is billed under the VGI rate, a dynamic hourly rate that incorporates day-ahead market prices, distribution cost recovery, and adders for the top 150 system load hours and top 200 distribution circuit load hours.

1.1 KEY FINDINGS

The impacts due to VGI prices were analyzed under two paradigms: an event-based analysis and a price elasticity analysis. The event-based analysis treated time periods when the system peak adder or distribution circuit peak adders were in effect as events. The event-based analysis estimates the treatment effect of the adders. The price elasticity analysis estimates the degree to which a change in prices leads to a change in loads.

Table 1 summarizes the results of the price sensitivity analysis. The elasticity in percentage terms is given by multiplying the price elasticity estimate in the second-to-last column by 100%. When drivers were charged, drivers were responsive to price and reduced demand by between 2.8% and 3.4% for a 10% increase in price. The estimates are statistically significant at the 1% level. They are slightly higher than estimates of the short-run residential price elasticity of demand for electricity; but are very similar to recent estimates of the short-run price elasticity of demand for gasoline. At rate-to-host sites, where the host paid for charging, we estimate a small, positive price elasticity. This estimate is largely driven by a single large site, and the estimate is statistically indistinguishable from zero for other sites. The price elasticity findings imply that electric vehicle charging is more price-sensitive to time-varying rates than whole building household electric loads.

Table 1: Price Elasticity Estimates Summary

Sector	Sites	Obs.	Price Elasticity	Std. Err
Rate-to-Driver Workplace	92	3,222,188	-0.341***	0.0538
Rate-to-Driver MUD	79	2,769,091	-0.283***	0.0394
Rate-to-Host	51	1,745,116	0.129***	0.0402
Rate-to-Host (Omitted Site 1132)	50	1,710,063	-0.005	0.0318

Note: *** p<0.01, ** p<0.05, * p<0.1.

Table 2 shows participants' aggregate and average load impact during the top 5, 10, and 20 load days for CAISO Gross Loads, CAISO Net Loads, and SDG&E Gross Loads. On the top 5 load days for CAISO Gross loads, participant loads peaked at 17.9 MW, and participants curtailed peak period demand by 3.6 MW in aggregate. For the top 5 load days for SDG&E Gross loads, participant loads peaked at 18.9 MW, and participants curtailed peak demand by 3.2 MW in aggregate. Load reductions are estimated relative to a counterfactual TOU rate that is revenue neutral.

Table 2: Ex-post Demand Reductions on Highest System Load Days (4-9 PM)

System	Month	Total Sites	Daily avg. temp ^[2]	Avg. Customer (kW)			Load Impact (MW)
				Reference Load	Load Impact	% Change	
CAISO Gross Loads	Top 05 load day(s)	219	77.8	81.66	-16.40	-20.1%	-3.59
	Top 10 load day(s)	219	77.0	83.85	-11.35	-13.5%	-2.49
	Top 20 load day(s)	219	76.2	80.21	-8.23	-10.3%	-1.80
CAISO Net Loads	Top 05 load day(s)	219	77.8	81.66	-16.40	-20.1%	-3.59
	Top 10 load day(s)	219	76.7	83.79	-12.65	-15.1%	-2.77
	Top 20 load day(s)	221	75.9	80.14	-8.40	-10.5%	-1.86
SDG&E Gross Loads	Top 05 load day(s)	219	79.6	86.23	-14.67	-17.0%	-3.21
	Top 10 load day(s)	219	76.9	86.74	-14.09	-16.2%	-3.09
	Top 20 load day(s)	219	77.2	77.15	-10.01	-13.0%	-2.19

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

2 INTRODUCTION AND BACKGROUND

This report presents an analysis of SDG&E's Vehicle Grid Integration (VGI) rate. In preparation for growth in electric vehicles (EVs), SDG&E deployed an infrastructure program, Power Your Drive (PYD), focused on encouraging electric vehicle adoption by reducing barriers such as the expense and difficulty of installing charging equipment at multi-family dwellings (MUDs) and workplaces. Electric vehicle charging at these sites is billed under the VGI rate, a dynamic hourly rate that incorporates market prices, distribution cost recovery, and adders for the top 150 system load hours and top 200 distribution circuit load hours.

Dynamic rates are considered a passive form of load management. They encourage customers to shift their use from higher-priced periods to lower-cost periods but do not directly control the charging behavior of customers or vehicles.

2.1 PYD AND VGI RATE BACKGROUND

The PYD program and VGI rate were designed to reduce greenhouse gas (GHG) and local pollutant emissions, increase the adoption of EVs, and integrate EV charging with the electric grid through a dynamic hourly rate. The Commission authorized SDG&E to install Level 2 charging stations at workplaces and multi-unit dwellings (MUDs) such as apartments and condominiums. Installations were incentivized with an investment subsidy, where the subsidy rate was higher for MUDs than for workplaces, and in turn higher for locations in census tracts that were designated as SB 535 disadvantaged communities (DACs)¹. SDG&E has installed, owns, and maintains charging stations at over 220 sites. The program offers two billing options: rate-to-driver, where drivers' charging costs appear directly on their SDG&E bill; and rate-to-host, where drivers' charging costs are billed to the host of the charging site. The VGI rate only applies to the charging of the EV. It also relies on a unique dynamic rate, which consists of five main components:

- **The Commodity Rate component reflects day-ahead hourly market prices.** This is based on the California Independent System Operator (CAISO) day-ahead market price for energy supply.
- **The base delivery component.** The delivery component is designed to reflect the costs of the transportation system used to deliver energy from where it is generated 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.

¹ For information on SB 535 disadvantaged communities: <https://oehha.ca.gov/calenviroscreen/sb535>

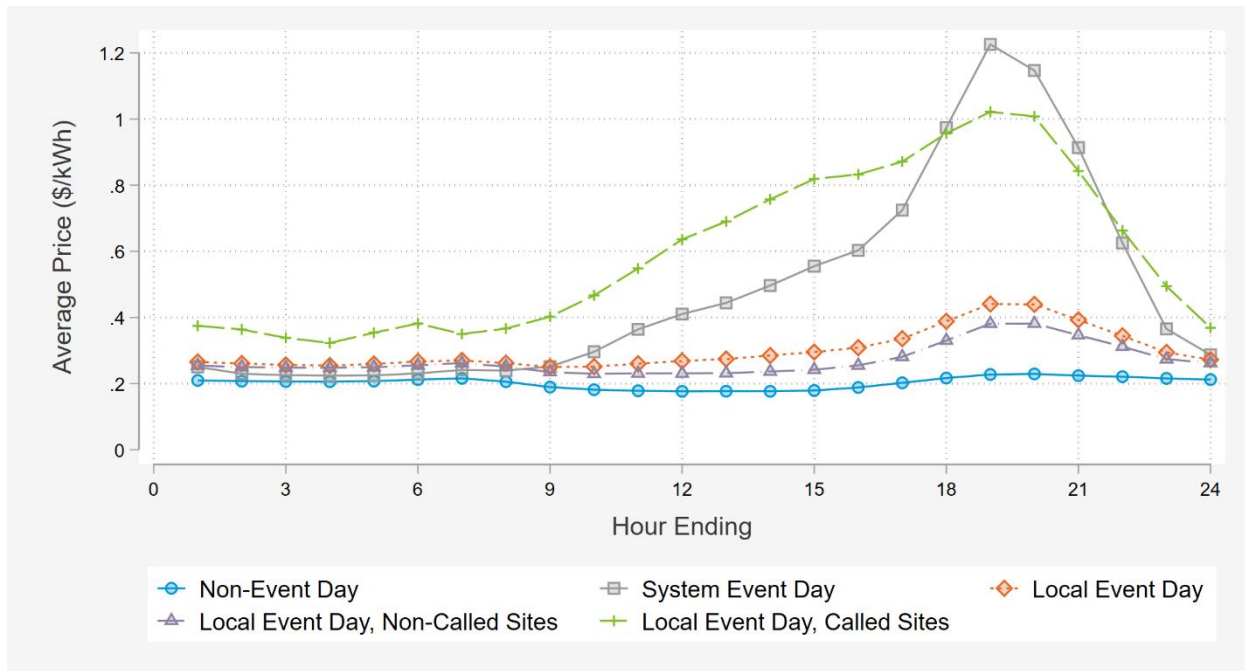
- ✓ A system adder that targets the top 150 system load hours (based on CAISO demand) to reflect the costs of generation capacity, which is needed to meet peak demand levels.
- ✓ A distribution rate adder or circuit adder targets the top 200 load hours of the distribution circuits that the charger is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

Figure 1 shows average hourly prices for PY 2022 through PY 2025 (10/1/2021—9/30/2025). We present average prices for five-day types:

- Non-event days, defined as days when no system event was called.
- System event days, defined as days when a system event was called (and all sites face system adders).
- Local event days, defined as days which a local event is called on at least one site.
- Local event days for non-called sites, defined as sites that were not called for local events on local event days.
- Local event days for called sites, defined as sites that were called for local events on local event days.

The highest hourly prices are on system event days, when all sites face system adders. Often, on system event days, some sites will also face local adders. Prices for called sites on local event days are also high, reaching \$1/kWh in hour ending 19. Local event day prices for called sites are higher than system event day prices in the morning and daytime hours because local events tend to be called earlier in the day than system events. Note that for both system event days, and local event days for called sites, because both start time and duration varies across events, these hourly average prices represent weighted average of prices across hours with and without events. Local event day prices, while higher than local event day prices for non-called sites, are still relatively low, because on many local event days only a small subset of sites are called. The lowest prices are on non-event days, when neither system events nor local events occur. The price on these days is about \$.20/kWh but varies across hours and is lowest during midday.

Figure 1: Average Hourly Prices by Day Type for PY 2022-PY 2025



The remainder of this section provides context and additional detail about the VGI rate. It details the key research questions, summarizes 2022-2025 grid conditions, presents the Vehicle Grid Integration participation and rates, and the utilization of the charging stations.

2.2 RESEARCH QUESTIONS

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

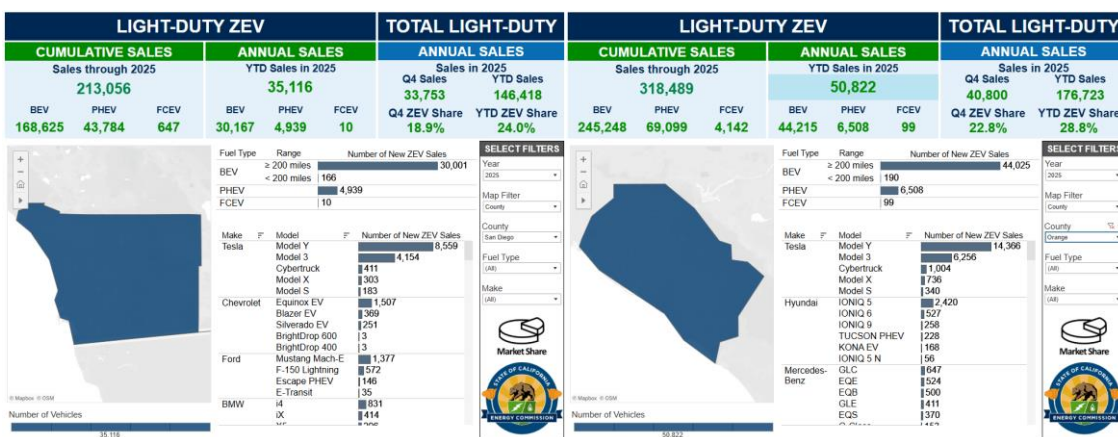
- How many charging stations are enrolled by customer type, and how has this changed over time?
- What is the utilization of charging stations by customer segment (rate-to-driver, rate-to-host, MUD, workplace, DAC, non-DAC, workplace type)?
- What was the load shift in 2025 under the VGI rate, including adder events?
- How do weather and market prices influence the magnitude of customer response, if at all?
- What is the customer awareness of different price signals?
- How do load impacts vary for different customer sizes, locations, and customer segments?
- What is the ex-ante load reduction capability under resource adequacy planning conditions?
- What concrete steps can be undertaken to improve program performance?

2.3 KEY FACTS ABOUT ELECTRIC VEHICLES IN SDG&E

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

As of December 2024, over 2.9M² vehicles were registered with the California DMV in SDG&E's service territory, which includes all of San Diego County and portions of South Orange County. Over 170,000 electric vehicles and 47,000 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 grew exponentially until 2023, and stagnated in 2024, as shown in Figure 2. In 2025, the market share fell slightly. Focusing on San Diego County (Figure 1, left panel), 24% of new vehicle sold were either full electric vehicles or plug-in hybrid vehicles, slightly lower than 2024. The historical market share penetration data has matured enough that vehicle share adoption can be estimated using historical data, as shown in Figure 2. This estimation of future market share relies on simple methods and historical data. Recent macroeconomic factors, and potential changes in state and federal policy, present a significant headwind to EV adoption. Higher interest rates tend to affect EVs more than other vehicles because they have a high up front cost and lower operational cost. Tax credits for EVs passed under the Inflation Reduction Act of 2022 (IRA) and vehicle emissions standards that benefit EVs have been weakened. These changes have begun to be reflected in sales, as demonstrated in the fall in market share in 2025.

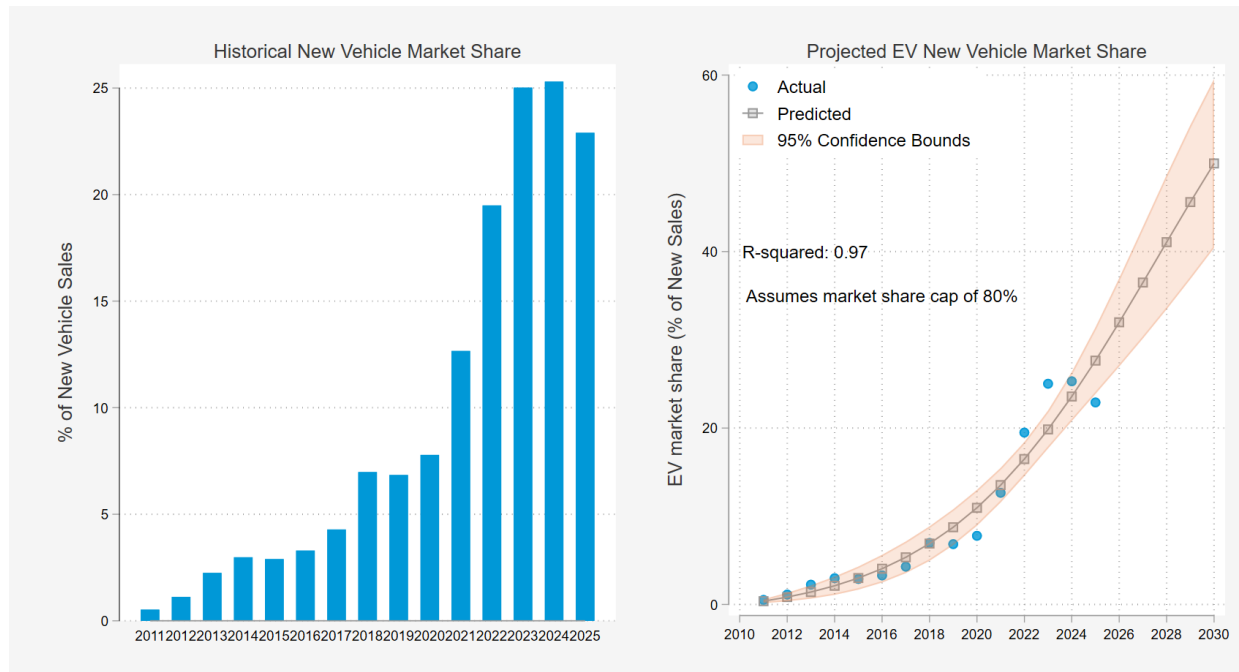
Figure 2: Electric Vehicle Population in SDG&E Territory (2025)



Source: California Energy Commission (2025). New ZEV Sales in California. Data last updated December 31, 2025. Retrieved February 4, 2026, from <https://www.energy.ca.gov/zevstats>

² Source: California Energy Commission (2024). Data last updated January 31, 2025. Retrieved February 15, 2025.

Figure 3: Electric Vehicle Market Share of New Vehicle Sales in California



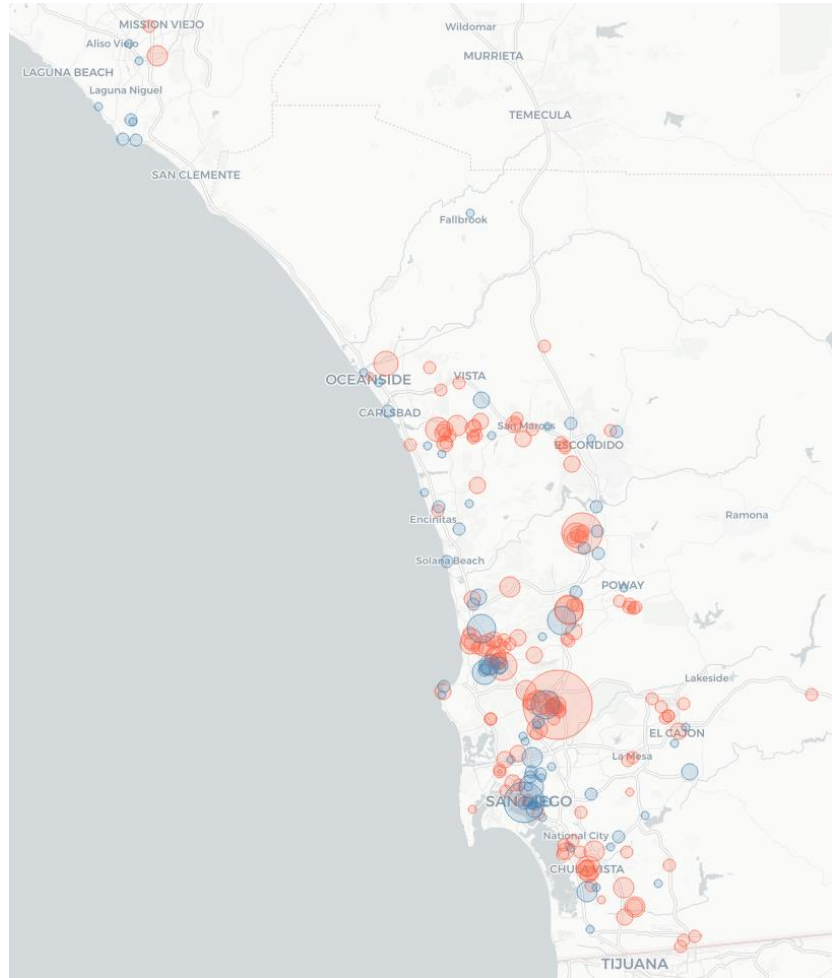
Data source: California Energy Commission (2025). New ZEV Sales in California. Retrieved February 4, 2026, from <https://www.energy.ca.gov/zevstats> Graphs and market share projection produced by DSA.

In preparation for growth in electric vehicles, SDG&E deployed an infrastructure program with a focus on encouraging EV adoption by reducing barriers such as the expense and difficulty of installing charging equipment at multi-family dwellings (MUDs) and workplaces. Figure 4 shows the location of sites installed in SDG&E territory, where MUD sites are shown in red and workplace sites are shown in blue. Sites are weighted by the number of ports at a site, where the largest sites have over 100 ports. Excluding a handful of sites that lack information on ports, SDG&E has deployed 2,783 charging ports at 217 sites. A total of 36% of the sites are located at MUDs, and 6% of sites are in disadvantaged communities. Nearly all the charging ports are Level 2 chargers.

Figure 4: SDG&E Vehicle Grid Integration Electric Vehicle Chargers

KEY FACTS

- There are 217 sites with port data available, representing 2,783 ports. This analysis uses site-level interval data for 222 sites in total.
- 171 sites are registered for rate-to-driver billing, representing 77% of the total 222 sites analyzed.
- 80 sites are located in MUDS, representing 36% of the total.
- 13 sites are located in disadvantaged communities (DACs), representing 6% of the total.



2.4 2025 GRID CONDITIONS

SDG&E delivers electricity to 3.7 million people in San Diego and southern Orange counties. It has 1.5 million residential and business accounts, a service area that spans 4,100 square miles, and a peak demand of over 4,000 MW³. 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.

³ SDG&E system load peaked at 4,022 MW on Tuesday September 2 at 6:45 PM.

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, 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 VGI rate encourage customers to shift usage to lower-priced hours when the electric grid is not peaking.

Figure 5 shows the hourly load pattern for the ten highest load days for SDG&E, CAISO, and CAISO net loads. SDG&E load peaked at 4,022 MW, CAISO load peaked at 43,921 MW, and CAISO net loads peaked at 40,129 MW. Figure 6 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. The need for generation capacity resources is highly concentrated. If targeted precisely, shaving loads on the top 1% of hours at SDG&E would lead to an 16% reduction (585 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 17% reduction (~5,927 MW) in need for generation capacity. Figure 7 shows the hourly electricity market prices for the SDG&E area from May to September 2025. The high price periods coincided with times when CAISO net loads were highest.

Figure 5: SDG&E and CAISO Top Ten Peak Load Days (Oct 2024-Sep 2025)

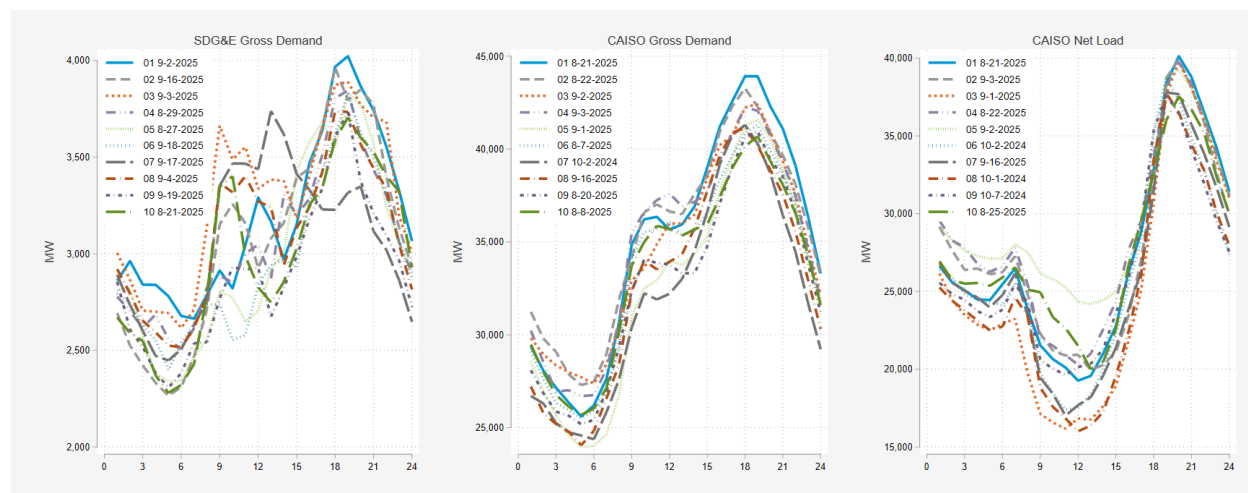


Figure 6: Normalized Load Duration Curves for Top 5% of Hours (Oct 2024-Sep 2025)

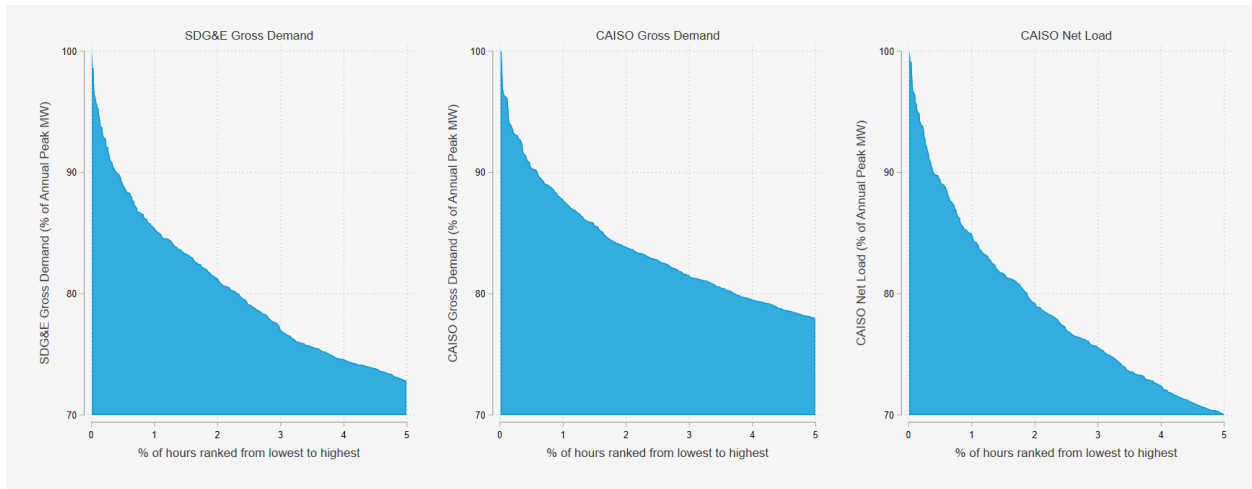
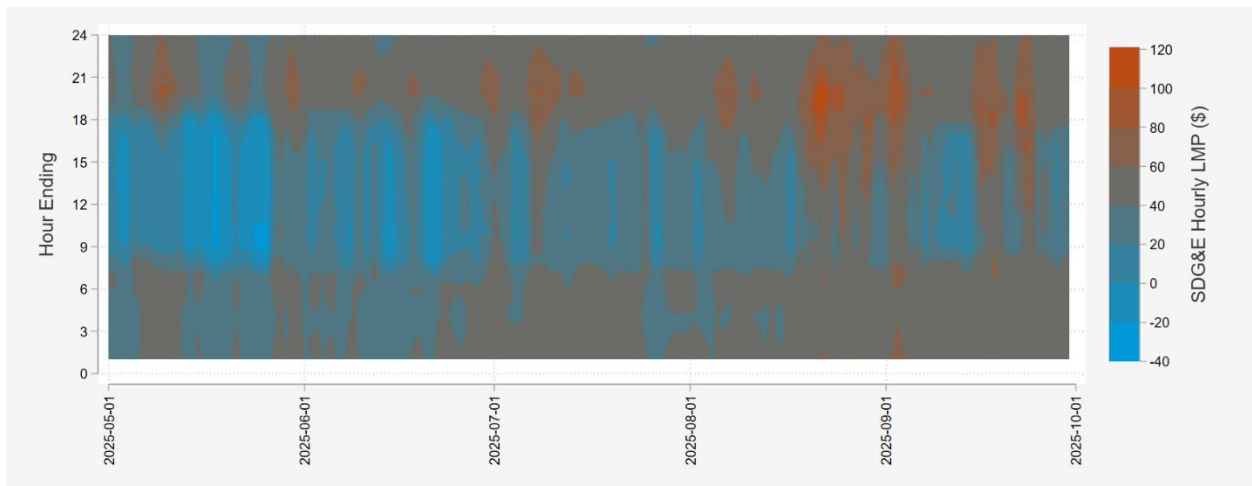


Figure 7: SDG&E Summer 2025 Hourly Electricity Market Prices



3 DATA

Our analysis data contains site-level charging interval data for all Power Your Drive sites for which data was available. We received at least some interval data for 269 sites in total. We then removed 13 sites that were missing interval data, which left 256 sites. After merging site characteristics identifying rate-to-host and rate-to-driver sites, among other features, we excluded sites that lacked characteristics and those that were not on the VGI rate during the analysis period. The remaining dataset contained 222 sites.

3.1 PREPARATION OF THE ANALYSIS DATASET

Preparation of the analysis dataset required that we convert site-level data to a panel dataset at the site-hour-level and fill in hours with zero demand that are unobserved in the interval data. Keeping only the intervals when charging occurred would result in biased estimates of price- and event-response because it would likely exclude high price times when drivers had chosen not to charge. The interval data contains some observations when a driver is not charging, where we observe zero demand at a site, but we cannot observe whether the driver had not yet begun charging or was choosing not to charge because the price was too high. We therefore construct a panel dataset by including site-hour observations when no charging occurred and merging in the price a driver would have faced in that hour had they been charging. Every hour at every site has a price a driver would face if they were charging.

3.2 SUMMARY STATISTICS

Table 3 shows summary statistics for the analysis dataset for program years 2022 to 2025 (October 1 2021 through September 30 2025). The data are at the site-hour-level. Average demand is 47.4 kWh for rate-to-driver workplace sites and 61.3 kWh for rate-to-driver MUD sites, and 132.22 kWh for rate-to-host sites. Demand at rate-to-host sites is highly variable, with a standard deviation of about 600 kWh. This is largely due to the presence of a small number of very large sites. The second row, "kWh > 0" shows the proportion of hours with positive demand, over 80% of hours. Dividing demand by the proportion of hours with positive demand yields demand conditional on vehicle charging, which is between 60 and 70 kWh for rate-to-driver sites, depending on site type. System and local events are rare, making up just 1-2% of observations. The average price is about \$0.25, but price has a relatively large standard deviation of about \$0.18 and can be as high as over three dollars. Average hourly temperatures are mild, about 62 degrees Fahrenheit. Some extremes are observed in the sample, as high as 111 degrees and as low as 22 degrees.

Table 3: Summary Statistics for Analysis Dataset

		Mean	SD	Min	Max
RTD, Workplace	kWh	47.41	189.88	0	4,950
	kWh > 0	0.83	0.38	0	1
	System Event	0.02	0.14	0	1
	Local Event	0.01	0.11	0	1
	Price (\$/kWh)	0.25	0.18	0	3.44
	Hourly Temp. (F)	62.67	9.01	22.82	111.74
RTD, MUD	kWh	61.30	211.08	0	6,182.40
	kWh > 0	0.90	0.30	0	1
	System Event	0.02	0.14	0	1
	Local Event	0.01	0.10	0	1
	Price (\$/kWh)	0.25	0.18	0	2.98
	Hourly Temp. (F)	62.72	9.36	22.82	111.74
RTH	kWh	132.22	836.52	0	19,552
	kWh > 0	0.84	0.36	0	1
	System Event	0.02	0.14	0	1
	Local Event	0.01	0.10	0	1
	Price (\$/kWh)	0.25	0.18	0	3.44
	Hourly Temp. (F)	62.36	10.54	22.82	111.74

Note: Rate-to-driver, workplace has 3,225,152 observations. Rate-to-driver, MUD has 2,769,424 observations. Rate-to-host has 1,745,307 observations.

All PYD SDG&E chargers installed are billed on SDG&E's VGI electric rate. The unique billing scheme is designed to encourage drivers to charge when there is abundant capacity on the grid. In particular, drivers are subject to Commodity Critical Peak Pricing (C-CPP) and the Distribution Critical Peak Pricing (D-CPP) components, referred to as system events and local events. During a system event, an hourly adder of \$0.86 is in place, and during local events, an hourly adder of \$0.77 is in place. Figure 8 shows a heat map of the proportion of sites subject to system events by hour and date for PY 2025. When a system event is in place, all sites are subject to the event. Figure 9 shows a heat map of the proportion of sites subject to system events by hour and date for historical program years. California experienced multiple heat waves and high-priced periods in 2022, which triggered system events. 2023 was milder, with system events occurring less often and across a narrower range of hours. System events tend to occur in the early evening. 2024 had more system and local events than 2023, particularly in August and September.

Figure 8: Share of Sites Subject to System Events by Date and Hour, PY 2025

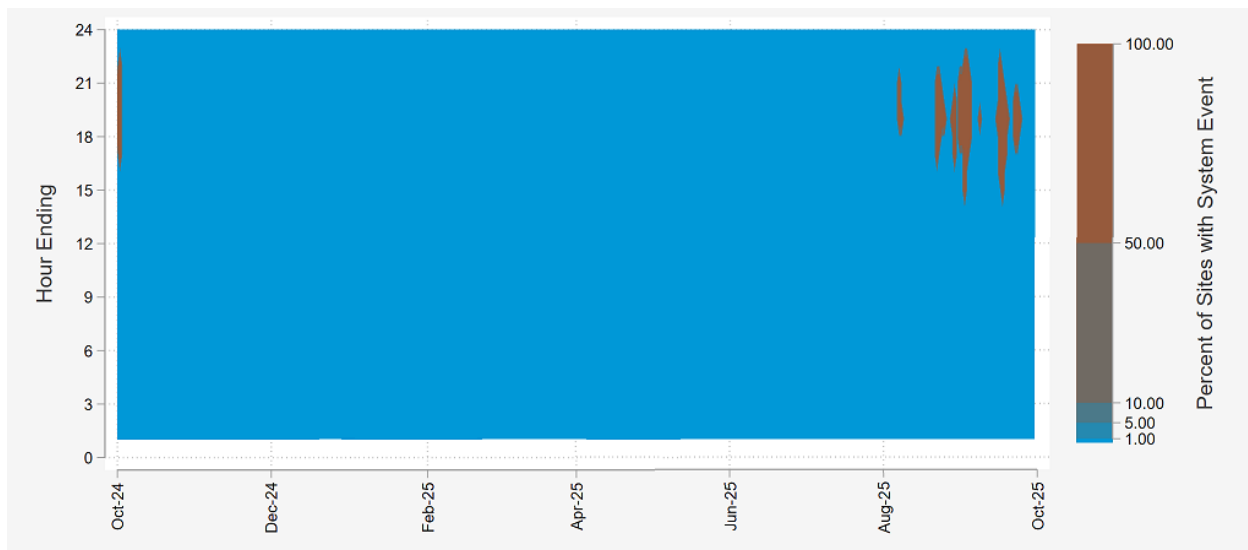


Figure 9: Share of Sites Subject to System Events by Date and Hour, PY 2022-PY 2024

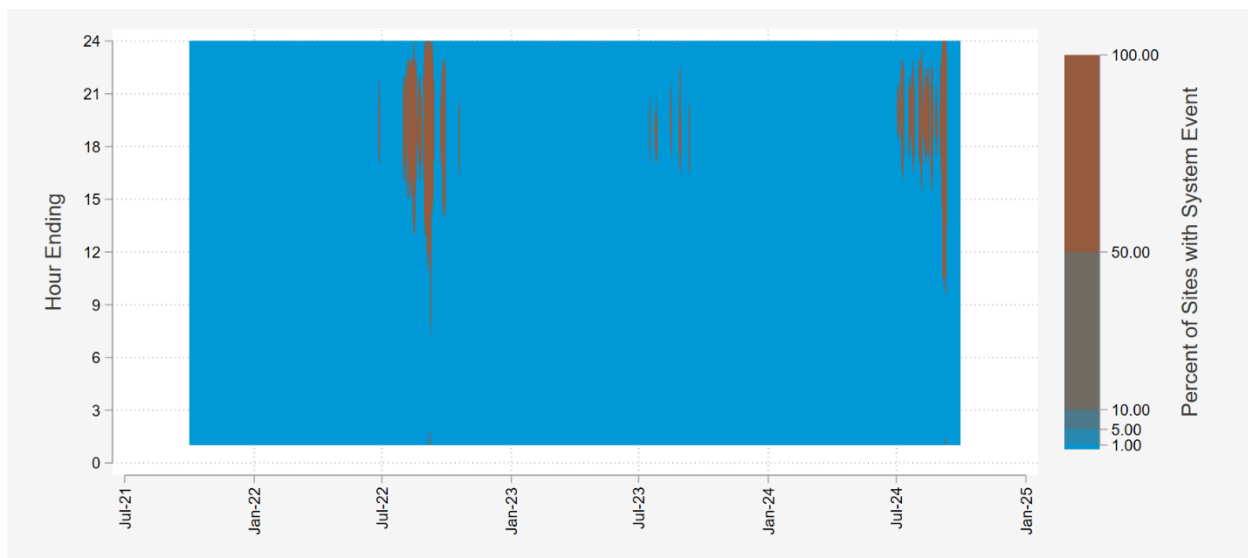


Figure 10 shows a heat map of the proportion of site subject to local events by hour and date for historical program years. There were no local events in PY2025 except for in October 2024 at a small number of sites. In contrast to system events, which are either in place for all sites or none, the share of sites subject to local events is often somewhere between 0 and 100. Before summer 2022, a small share of sites were subject to system events in the winter and spring. During summer 2022, when multiple heat waves occurred, local events spanned more hours than system events. In that period, system events and distribution events are correlated: they were often called on many sites when system events were called. In February of 2023, a billing error resulted in local events across many sites for many hours. Those bills were refunded, but customers faced prices and were unaware they would eventually be refunded. A small portion of sites was often subject to local events in the morning and evening

throughout the spring and summer of 2023. In 2024, fewer local events were called than in the summer of 2022. Overall, note that prior to 2024, local events are often called at times and dates when system events are not called. In the summer of 2024, the occurrence of local events seems more correlated, at least temporally, with system events, than in the past. In general, there exist many periods when local events occur when system events do not, and there are some periods when system events occur when local events do not, these data will allow us to separately identify the effects of system and local events. This remains true in 2024, since the share of sites with local events tends to be low when local events are called.

Figure 10: Share of Site Subject to Local Events by Date and Hour, PY 2022-PY 2024

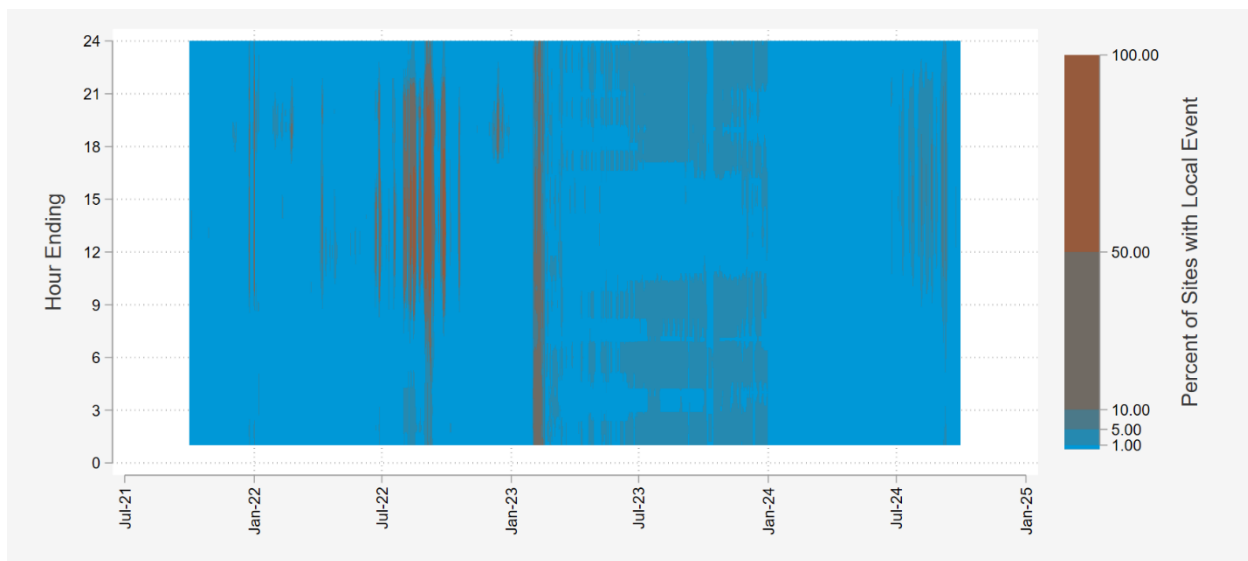
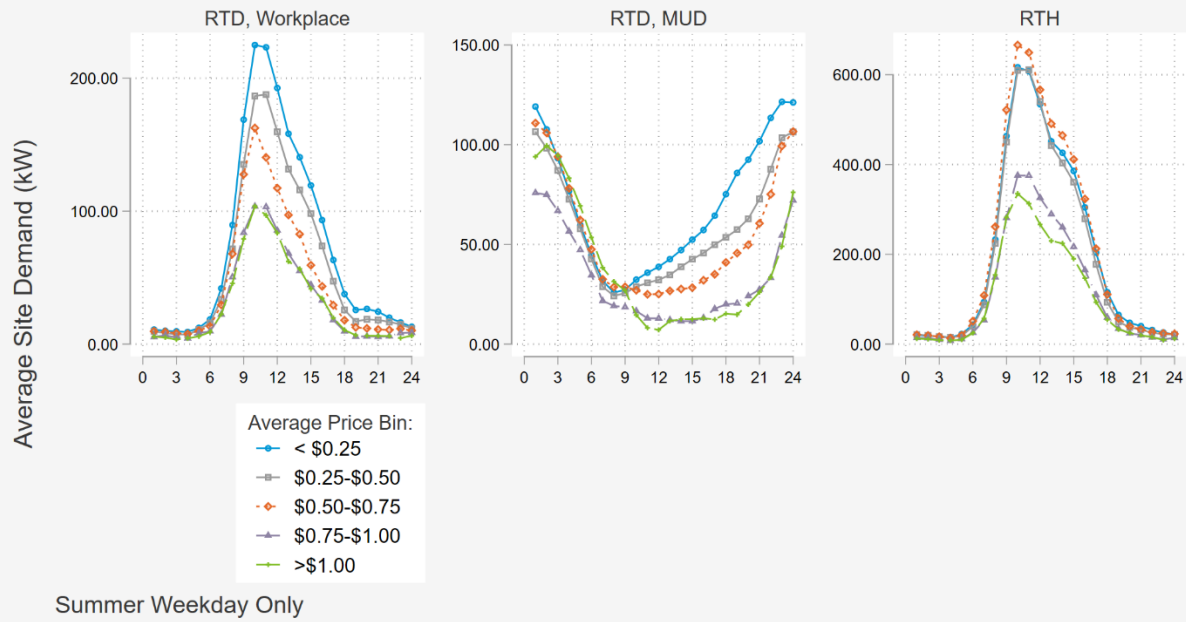


Figure 11 shows average hourly consumption patterns by average daily price discretized into bins for 2022-2025 summer weekdays by the site type. The relationship between price and charging patterns is very clear for rate-to-driver sites. In general, when prices are high, vehicle charging decreases. For MUD sites, a shift of loads to overnight hours when prices are low is evident. There is little evidence of shifting at workplaces because there is little load during evening hours. Rather than shift usage, drivers likely substitute home charging for workplace charging on high-price days. When workplaces do not charge the driver (middle panel), it is difficult to identify any relationship between prices and load.

Figure 11: Average Site Load by Daily Average Price



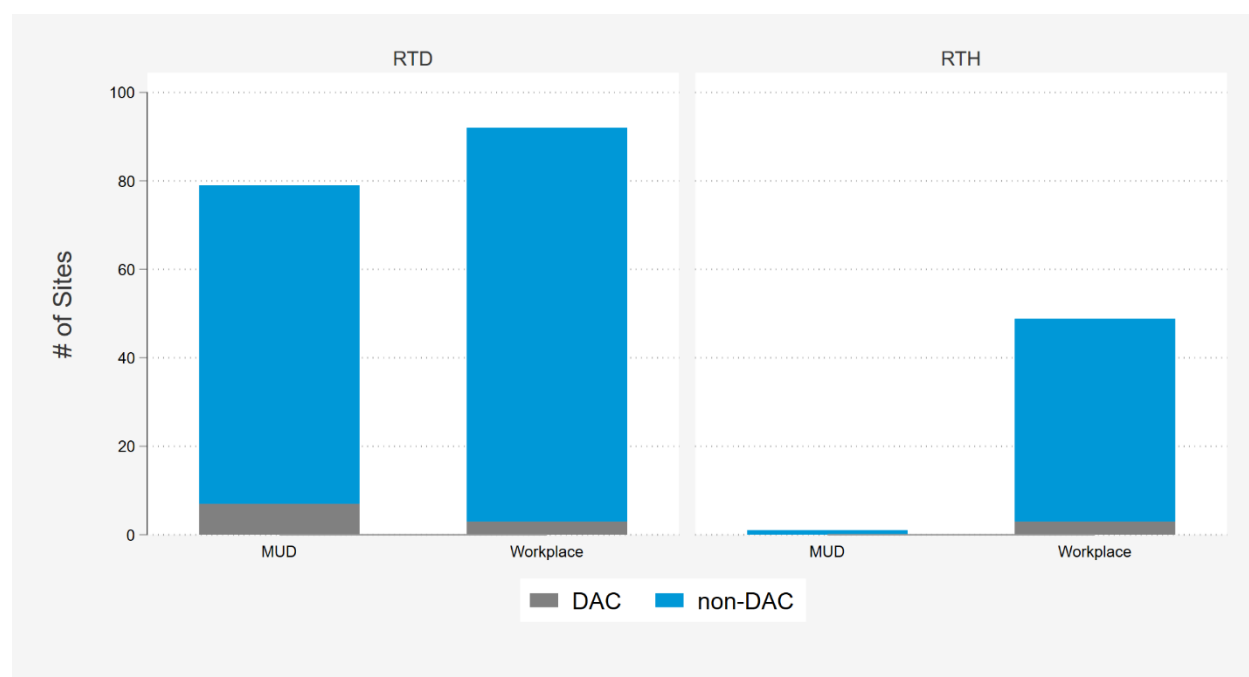
4 PROGRAM DEPLOYMENT AND UTILIZATION RESULTS

In this section, we analyze enrollment and utilization trends for the VGI rate.

4.1 ENROLLMENT BY CUSTOMER TYPE

Figure 12 plots the number of enrolled sites by customer type for program years 2022 to 2025. (The number of sites has not changed meaningfully over the analysis period.) The left panel shows rate-to-driver sites, and the right panel shows rate-to-host sites. Each is broken out by whether the site is a MUD or workplace as well as whether the site falls in a DAC. Overall, about half of the rate-to-driver sites are workplace sites, whereas rate-to-host sites are almost entirely workplace sites. Despite the offer of a higher investment subsidy for VGI sites installed in DACs, few of the enrolled sites are located in DACs.

Figure 12: Enrolled Sites by Customer Type



4.2 UTILIZATION

Figure 13 plots the weekly average load shape for rate-to-driver sites. The graph shows observed load for program year 2024 (October 1, 2022 through September 30, 2025), and includes all hours, including event hours. Overall, load at MUD and workplace sites is negatively correlated. MUD charging load tends to peak in the late evening or early morning when workplace charging load is very low. Conversely, workplace charging load tends to peak at midday when MUD charging load is relatively low. As expected, workplace charging load is very low on weekends. MUD charging load is largely

similar on weekends and weekdays. Workplace load is slightly peakier than MUD load, perhaps consistent with fairly uniform arrival times at charging stations across workplace locations relative to MUD locations, which you would expect to vary with users' commute times.

Scrutiny of these load patterns allows us to draw conclusions about the potential for demand reductions depending on when events are called. If an event is called at midday, there is little MUD charging load, so we would expect small demand reductions. However, if an event is called in the early evening, as tends to be the case for system events, there is more MUD charging load to curtail. For workplaces, where load tends to peak at midday, we expect small reductions for evening events and larger reductions for events called in the daytime, often when local events are called.

Figure 13: Average Site Weekly Load Shape for Rate-to-Driver Sites

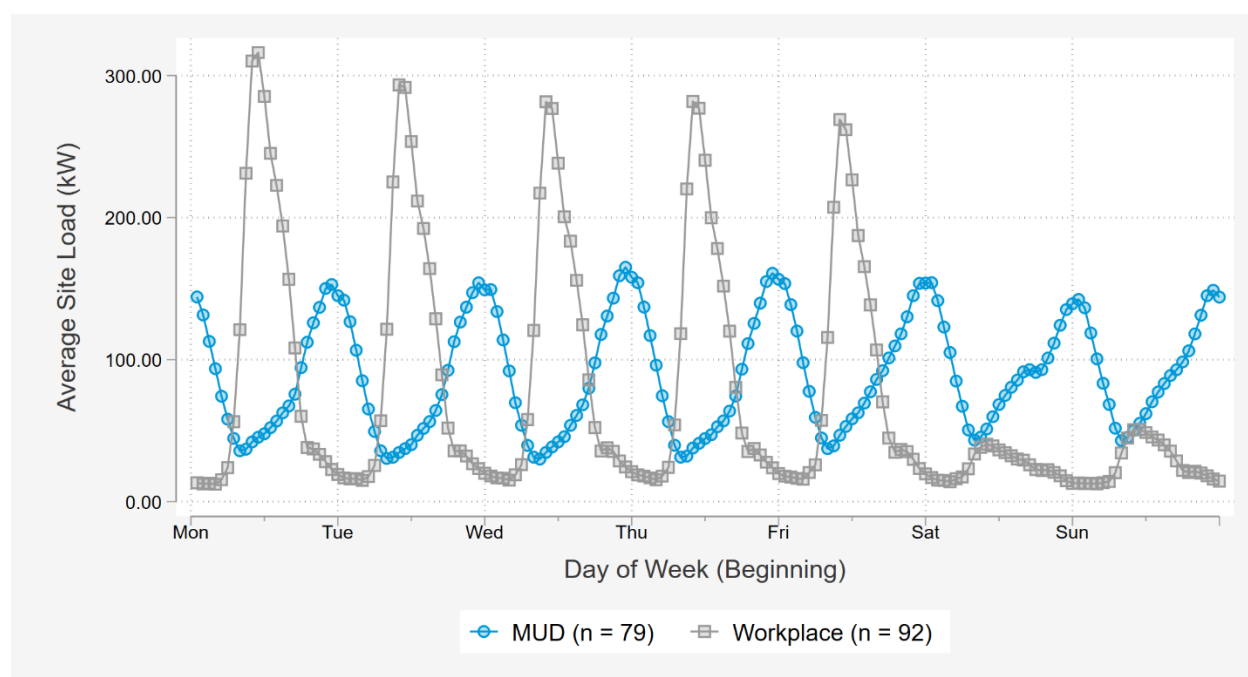
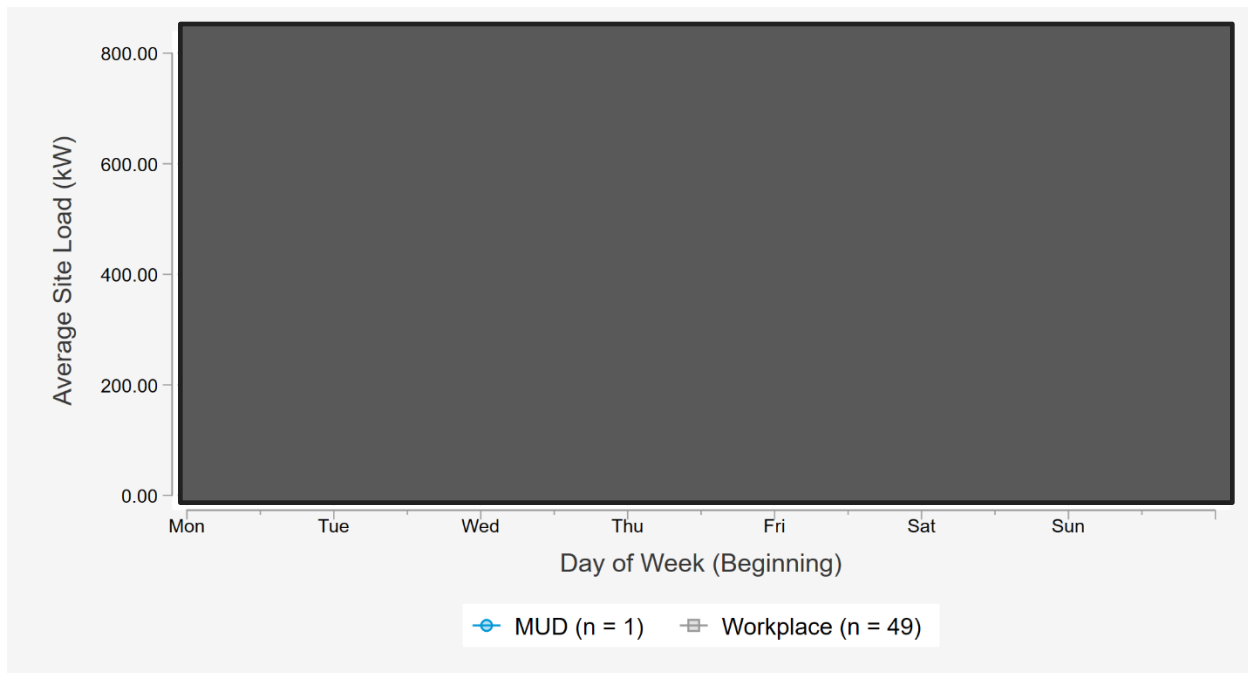


Figure 14 plots the weekly average load shape rate-to-host sites. The graph shows the observed load for program year 2024 (October 1 2022 through September 30 2025), and includes all hours, including event hours. There is a single MUD site whose charging load appears similar to that of workplace sites, yet at a smaller scale, so we caution against drawing inferences from a single site of any type. The load shape at workplace sites at rate-to-host sites looks very similar to the load shape at rate-to-driver sites in Figure 13 above. The level of peak load at rate-to-host sites is higher than at rate-to-driver sites. This likely reflects a combination of factors, including less price sensitivity and higher utilization at rate-to-host sites.

Figure 14: Average Site Weekly Load Shape for Rate-to-Host Sites⁴



In Figure 15, we plot monthly consumption for average rate-to-driver sites for each type of site. First, note that the average site monthly consumption at MUD sites is larger than the monthly consumption at workplace sites. Aside from differences in number of charging ports, which we do not observe, a possible mechanism for this discrepancy is that customers charging at the workplace have more options – most EV drivers can access level 2 charging stations at home. Conversely, most workplaces do not offer EV charging, so drivers charging at MUDs likely do not have workplace charging. Consumption at both workplaces and MUDs is increasing over time, as the number of sites remains constant over time. Consumption at DAC sites is below that at non-DAC sites for both MUDs and workplaces, likely due to smaller sites, in terms of number of ports, at DAC sites.

⁴ Grey Highlighted information is considered confidential and/or privileged information pursuant to applicable provisions of D.06-06-066, G.O. 66-D and PUC Code Section 583 and Section 454.5 (g),

Figure 15: Average Monthly Consumption for Rate-to-Driver Sites⁵

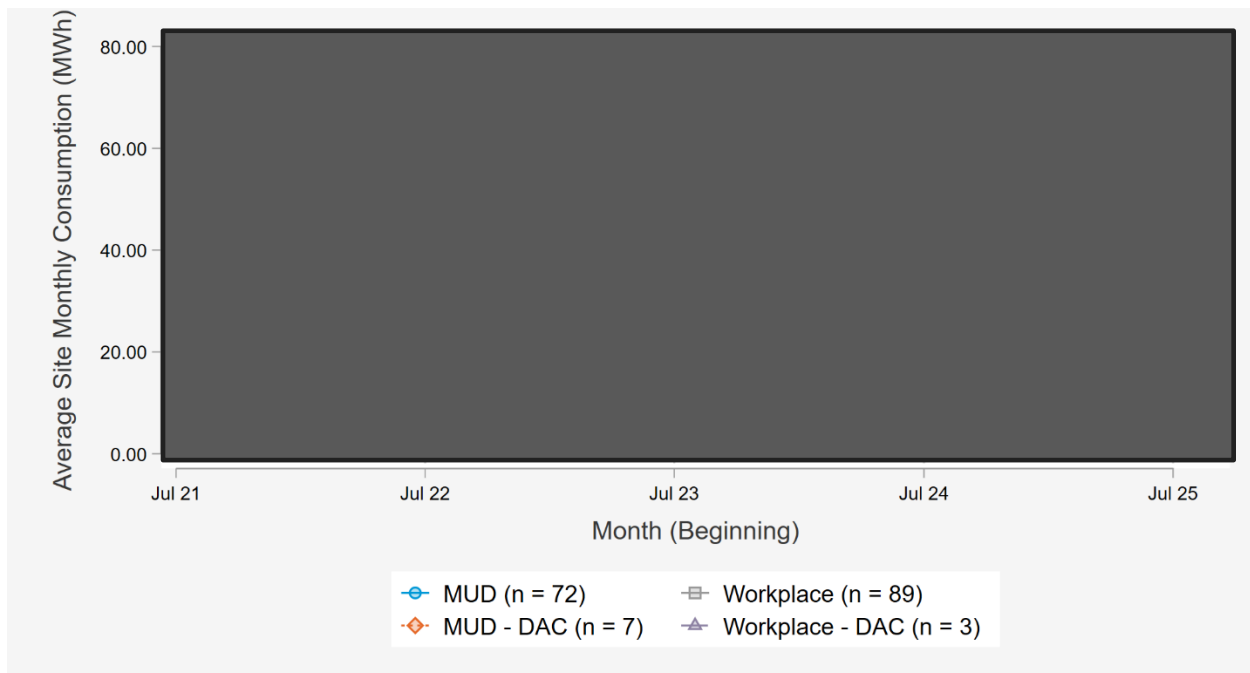
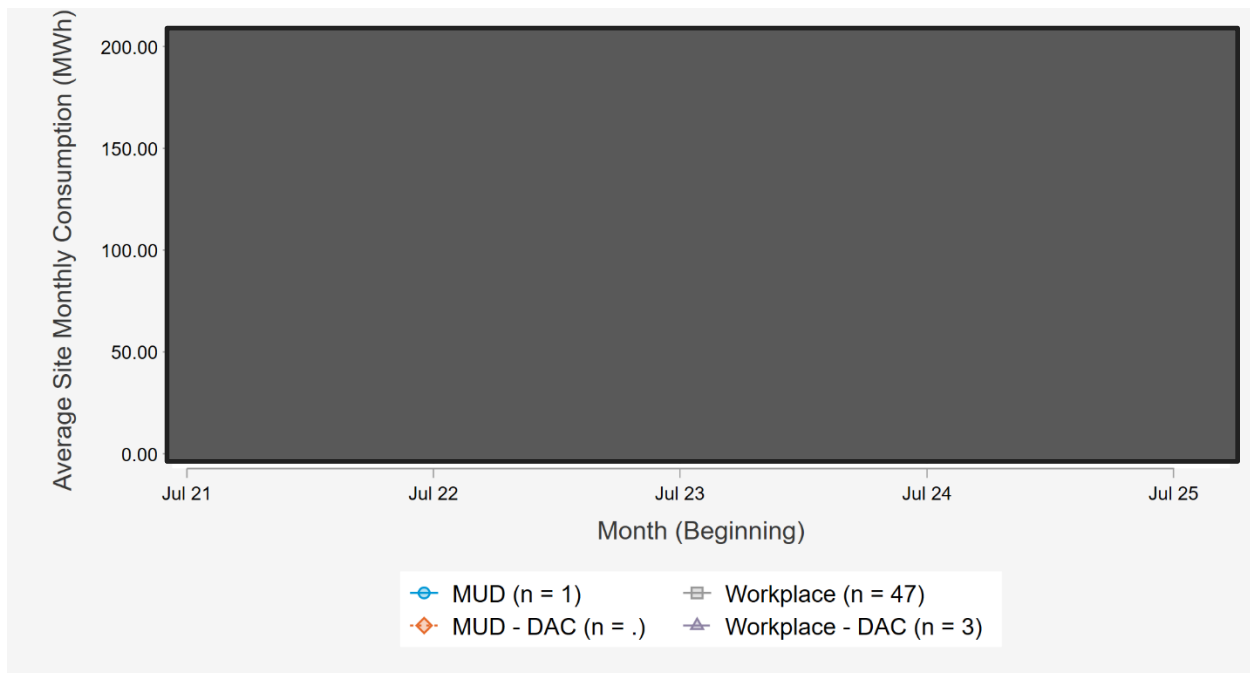


Figure 16 shows the monthly consumption for average rate-to-host sites for each type of site. Workplace consumption at rate-to-host sites is much higher than at rate-to-driver sites. Some rate-to-host sites are very large. It is also possible that at rate-to-host sites, drivers substitute all their charging demand to the free charging stations at their workplace.

⁵ Grey Highlighted information is considered confidential and/or privileged information pursuant to applicable provisions of D.06-06-066, G.O. 66-D and PUC Code Section 583 and Section 454.5 (g).

Figure 16: Average Monthly Consumption for Rate-to-Host Sites⁶



⁶ Grey Highlighted information is considered confidential and/or privileged information pursuant to applicable provisions of D.06-06-066, G.O. 66-D and PUC Code Section 583 and Section 454.5 (g).

5 METHODOLOGY

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

The key challenges that affect the evaluation are:

- **Potential endogeneity of price and events due to omitted variables.** Events and high prices are not randomly assigned but occur at times when peak conditions occur on the system and/or local distribution grid. These times could be related to charging behavior in unobservable ways that result in biased estimates. For example, during heat waves when high prices tend to occur, customers do not charge at work but instead take the day off and go to the beach.
- **Lack of a control group.** Many potential omitted variables could be accounted for if participant charging could be compared with charging for a control group made up of non-participants with access to Level 2 workplace and MUD charging stations that were not subject to the VGI rate. However, most Level 2 workplace and MUD chargers are enrolled in the SDG&E program, making it challenging to develop a control group that did not face the dynamic rates. Often, those that are not enrolled in the SDG&E program are not separately metered so charging load is confounded with other end uses. Our empirical strategy must use only participating PYD sites. We rely on both between- and within-variation to estimate the effects of interest. Because not all sites were subject to local events, we can compare sites that were and were not experiencing events in the same hour. We can also compare across time within a site.
- **Lack of pre-treatment data.** PYD sites owned and operated by SDG&E did not exist before the VGI rate. These sites were incentivized with an investment subsidy, and billing under the VGI rate was a condition of the program. This means pre-treatment data is not available and presents two challenges. Firstly even if a control group of untreated sites was available, load data could not be used to match the sites since we never observe PYD sites in an untreated state. Secondly, because they did not exist before the VGI rate, the choice of counterfactual rate for load reductions is not obvious.
- **Excess zero values.** For some segments, 20% observations in the data have zero consumption. Ordinary least squares (OLS) regression models that use transformations such as log and asinh are biased, particularly in the presence of excess zeros (King 1988). We present event result estimates in levels (kW) from an OLS regression and in percent terms from a Poisson regression. We present elasticity estimates from a Poisson regression.
- **Customer anticipation of events.** EV drivers receive advanced notice of adder events. Estimated reductions will be biased if anticipation effects (and rebound effects) are not controlled for, because the reference load, which includes estimates from the same hour on the day prior to (and after) an event, will be too high if the customer substitutes charging away from event hours to the same time on different days.

5.1 EX-POST EVALUATION APPROACH

Table 4 presents a summary of the ex-post evaluation approach.

Table 4: Vehicle Grid Integration Ex-Post Evaluation Approach Summary

Methodology Component	Demand Side Analytics Approach
1. Population or sample analyzed	Interval data for VGI sites from October 1, 2021 through September 30, 2025 were provided for the evaluation. We analyzed charging throughout this period to estimate price responsiveness. Load impacts are based on rates observed in the PY2025 period from October 1, 2024 through September 30, 2025.
2. Data included in the analysis	<p>For the VGI evaluation, we utilized:</p> <ul style="list-style-type: none"> Site-level interval 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	<p>We performed the following steps to estimate ex-post load impacts:</p> <ul style="list-style-type: none"> Estimated price elasticities for each site type (MUD rate-to-driver, workplace rate-to-driver, and rate-to-host). We used a panel regression with fixed effects and time effects that estimates the relationship between hourly prices and energy use at the site level. To produce load impacts, we assumed that charging load would have billed on an otherwise applicable rate, TOU-DR1, scaled to account for differences in revenue recovered. Impacts were computed for every hour and customer by using elasticities to predict load under the VGI rate, and under the counterfactual rate, and taking the difference. Then, for each day type (top n load days, monthly peak days, monthly average day) and customer segment, average impacts were estimated by averaging over the relevant hours and customer segments. <p>Separately, we estimated an event response model which treated periods with generation or distribution capacity adders as events. The event-based model flagged hours with local or system Critical Peak Pricing adders as events. We document that model and its estimates in the Appendix.</p>
4. Segmentation of impact results	<p>The results will be segmented by:</p> <ul style="list-style-type: none"> Site type: Workplace vs. Multi-Unit Dwellings Rate to Host vs. Rate to Driver

5.2 EMPIRICAL MODEL: PRICE ELASTICITY

To recover the causal effect of a change in price on charging demand, we employ a similar method to the estimation of relative effects in the event specification. We replace event variables that are described in Table 13 above with a single variable encoded as the natural logarithm of the price that

applies to a site for a particular hour. Formally, we again model kW_{it} as a Poisson random variable with parameter $\lambda_{it} > 0$. We model λ_{it} as an exponential function:

Equation 1: Price Elasticity Model Poisson Specification

$$\lambda_{it} = e^{W'_{it}\eta},$$

where,

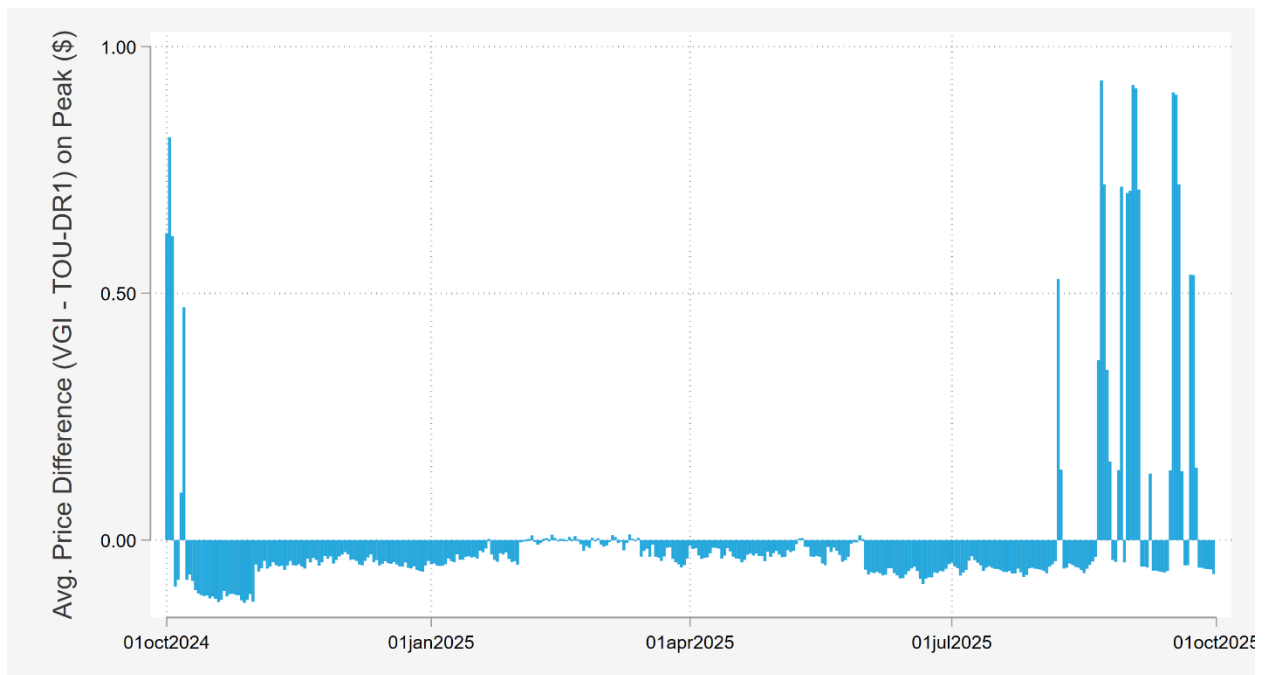
$$W'_{it}\eta = \gamma_1 \log(\text{Price})_{it} + \gamma_2 A_{it} + \gamma_3 R_{it} + \rho_{site} + \delta_{date} + \omega_{dow} + \tau_{temp} + \pi_{hour}.$$

The coefficient of interest is γ_1 , the elasticity of load with respect to price. The elasticity in percentage terms is given by $\gamma_1 \times 100\%$. We estimate the model separately for rate-to-driver workplace sites, rate-to-driver MUD sites, and rate-to-host sites to yield three distinct estimates of price elasticity. Standard errors are two-way clustered at the site, hour-of-sample level.

COUNTERFACTUAL RATE DEVELOPMENT

PYD sites owned and operated by SDG&E did not exist before the VGI rate. These sites were incentivized with an investment subsidy, and billing under the VGI rate was a condition of the program. Because sites did not exist before the VGI rate, the choice of counterfactual rate for load reductions is not obvious. We construct a rate that has the same price ratio as the TOU-DR1 rate, which is the default residential rate. We scale the TOU-DR1 to be revenue-neutral in PY2025 to account for the large difference in revenue recovered by each rate. Figure 17 shows the average price difference on peak between the VGI rate and the counterfactual scaled TOU-DR1 rate during PY2025. The VGI rate is much higher during summer peak days when system events were called and otherwise tends to offer a modest discount.

Figure 17: PY2025 VGI peak price surge relative to scaled tou-DR1 by date



5.3 EX-ANTE EVALUATION APPROACH

A key objective of evaluations is to quantify the relationship between changes in load, temperature, and hour-of-the-day. The purpose of doing so is to establish the load-shift capability under 1-in-2 and 1-in-10 weather conditions for planning purposes and, increasingly, for operations. Ex-ante impacts for PYD are distinct from those in most other evaluations because the rate itself is a real-time price which changes as a function of weather. On average, prices are expected to be higher during 1-in-10 weather year conditions than during 1-in-2 weather year conditions. Furthermore, charging load, and price responsiveness is not very weather sensitive, at least after accounting for price variation. There is also evidence that price-sensitivity is relatively constant across days with no events and days with events. These facts inform the key steps for estimating customer-level ex ante impacts, which are as follows:

- Use three years of historical load data and prices for the period from October 1, 2022 through September 30, 2025.
- Estimate the relationship between the VGI rate and weather conditions for each site.
- Use the rate-weather models to predict the VGI rate for 1-in-2 and 1-in-10 weather year conditions for each site.
- Incorporate enrollment forecast with forecast VGI rate, estimated price elasticities, counterfactual rate, to estimate reference loads and impacts per household.
- Ex-ante tables will be produced for the VGI rate in compliance with the load impact protocols.

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.

Our ex-ante enrollment forecast is equal to the current ex post enrollment. Enrollment has been constant in recent years. Pursuant to the Load Impact Protocol Process Guide (version 6.1, released by the Energy Division on March 5, 2026), large loads (e.g. data centers, EV fleet charging station load) should be reported as a distinct load type. Among VGI sites, we cannot separately identify fleet sites due to a mix of charging occurring at Workplace sites between fleets and employee personal vehicles. We report results separately for Workplace, Rate-to-Host sites, which likely includes some fleet charging.

EX-ANTE PRICE PREDICTION

The ex-ante impacts were developed by estimating the relationship between weather and demand reductions for sites on the VGI rate. Given that the real-time price is a function of weather, we predict future prices based on ex-ante weather conditions. We expect future prices to reflect historical prices, however due to the absence of local events in 2025 the overall VGI price this year was lower than historical prices. Therefore, we validated the price predictions according to a business-as-usual given that future program years will include both system and local events.

Figure 18 compares the average hourly event day ex-ante VGI price predictions for a typical event day to the PY2021-PY2025 historical VGI price, the 2025 VGI price, and the revenue adjusted TOU-DR1 rate. Ex-ante is more like the historical since it is an average of those prices, adjusted for ex-ante conditions.

Figure 19 compares the monthly worst day ex-ante VGI price predictions for a typical event day to the PY2021-PY2025 historical VGI price, the 2025 VGI price, and the revenue adjusted TOU-DR1 rate. We note that even on the worst day, VGI prices are only higher than the TOU-DR1 rate during summer months with a peak price observed in September.

Figure 20 compares the monthly average day ex-ante VGI price predictions for a typical event day to the PY2021-PY2025 historical VGI price, the 2025 VGI price, and the revenue adjusted TOU-DR1 rate. We note that the VGI price is still higher on the average weekday than TOU-DR1 during the summer with the highest average price observed in September.

Figure 18: VGI Price Prediction for SDG&E 1-in-2 Weather Year Typical Event Day

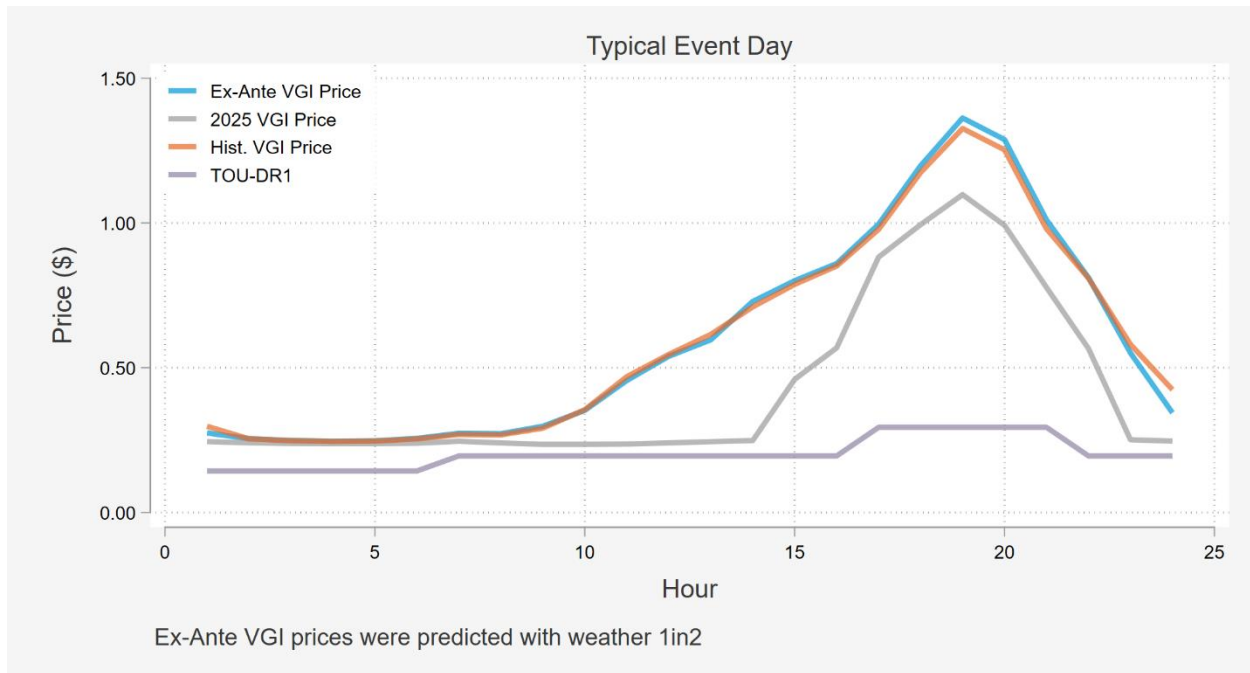


Figure 19: VGI Price Prediction for SDG&E 1-in-2 Weather Year Monthly Worst Day

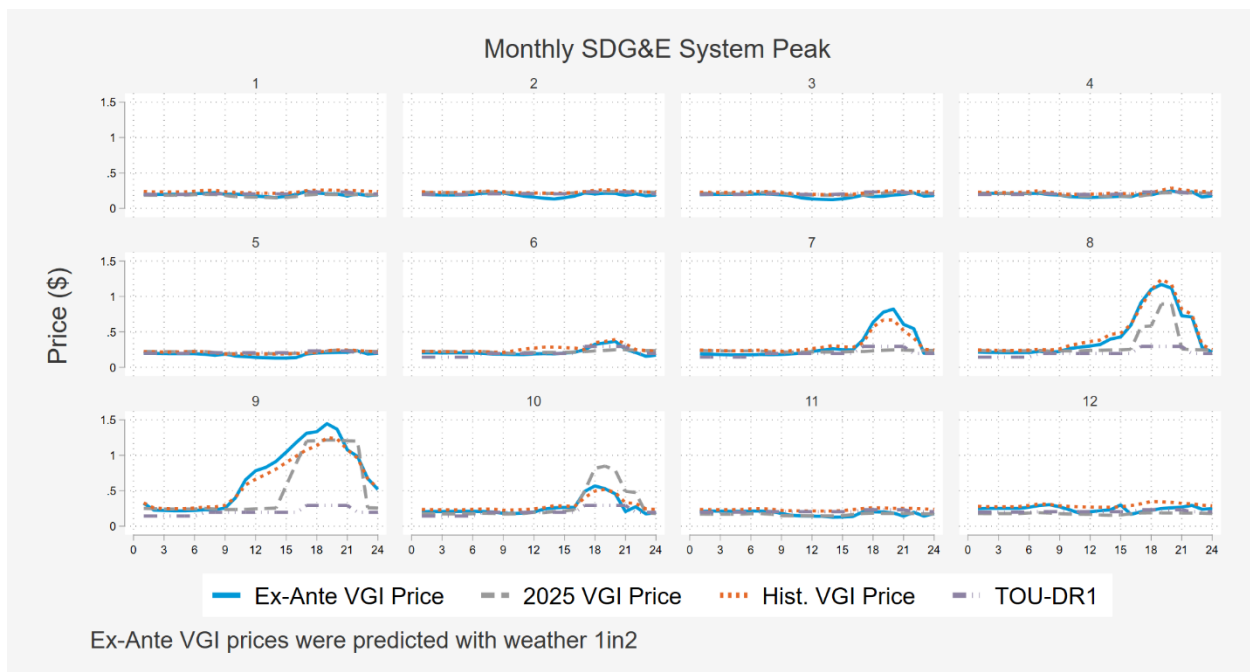
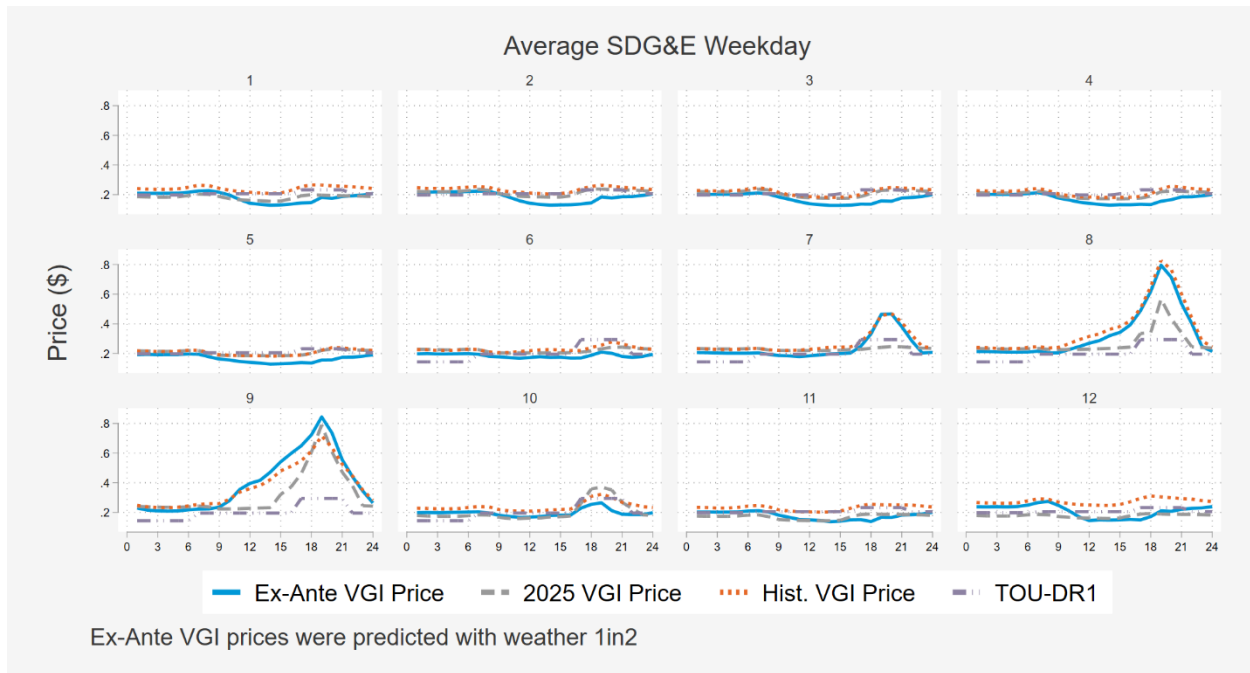


Figure 20: VGI Price Prediction for SDG&E 1-in-2 Weather Year Monthly Average Day



6 VEHICLE GRID INTEGRATION EX-POST RESULTS

This section presents estimates of charging response to the VGI rate delivered by drivers charging at Power Your Drive workplace and MUD charging stations. We estimate event-based load impacts in levels (kW) and in relative (%) terms. We estimate price response in terms of price elasticity of demand, defined as the percent change in load in response to a 1% change in price. Estimates are for the time frame October 1, 2021 through September 30, 2025.

6.1 PRICE SENSITIVITY

Table 5 presents estimated price elasticities for each site type. The table includes coefficient estimates and standard errors from three separate Poisson regressions: rate-to-driver, workplace estimates are presented in column (1); rate-to-driver, MUD estimates are presented in column (2); and rate-to-host estimates are presented in column (3). These estimates pool data from program years 2022 to 2025. The estimate of -0.341 at rate-to-driver workplace sites indicates that, on average, drivers decrease their charging by 3.4% for each 10% increase in prices. At MUD sites, the price responsiveness is slightly less. Drivers decreased their charging by 2.8% for each 10% increase in prices. These estimates are statistically significant at the 1% level. To our knowledge, other publicly available estimates of price responsiveness at level 2 charging stations do not exist at this time. These drivers are more responsive than the average residential electricity consumer, implying that electric vehicle loads are easier to shift than typical household loads. A meta-analysis of short-run price elasticity of electricity demand for electricity yielded an average estimate of -0.22 (Zhu 2018). However, modern applied research into consumer response to gasoline price fluctuations finds very similar estimates of price responsiveness. Recent short-run estimates of the price elasticity of gasoline demand have included -0.37 for U.S. drivers (Coglianese, et al. 2017), as well as between -0.27 and -0.35 (Levin, Lewis and Wolak 2017).

Columns (3) and (4) report estimates for rate-to-host sites where charging is free at the site for drivers and the VGI rate is paid by the site host. Column (3) presents results for all such sites, and column (4) presents results that omit a single site that is a large outlier in terms of maximum demand and average demand over the study period. Figure 21 plots site-level maximum demand and average demand over the study period. The outlying site that we remove is represented by the data point in the top right of the graph. In column (3), the estimated elasticity is small but positive and statistically significant at the 5% level. In column (4), which omits the outlying site, the estimated elasticity is smaller and not statistically significant. Taken together, these estimates suggest there is little evidence to conclude that drivers at rate-to-host sites were price-responsive. The finding of a positive⁷ elasticity in column (4) is largely the result of a single outlying site, and in any case, the estimate is small. Restricting to sites that are similar in size to the rest of the sample yields estimates that are small and statistically indistinguishable from zero. This serves as a check on our main specification. If we were to find

⁷ The finding of a positive elasticity for rate-to-host sites, suggests, if anything, that our baseline estimates for rate-to-driver sites are conservative, in that they potentially are downward biased and underestimate price sensitivity.

statistically significant negative price elasticities at rate-to-host sites, where there is no reason to expect drivers to respond to price⁸; we would be concerned our estimates for rate-to-driver sites were biased. The lack of price responsiveness is precisely estimated; we can rule out price elasticities below -0.016 based on the coefficient estimate and standard error in column (4).

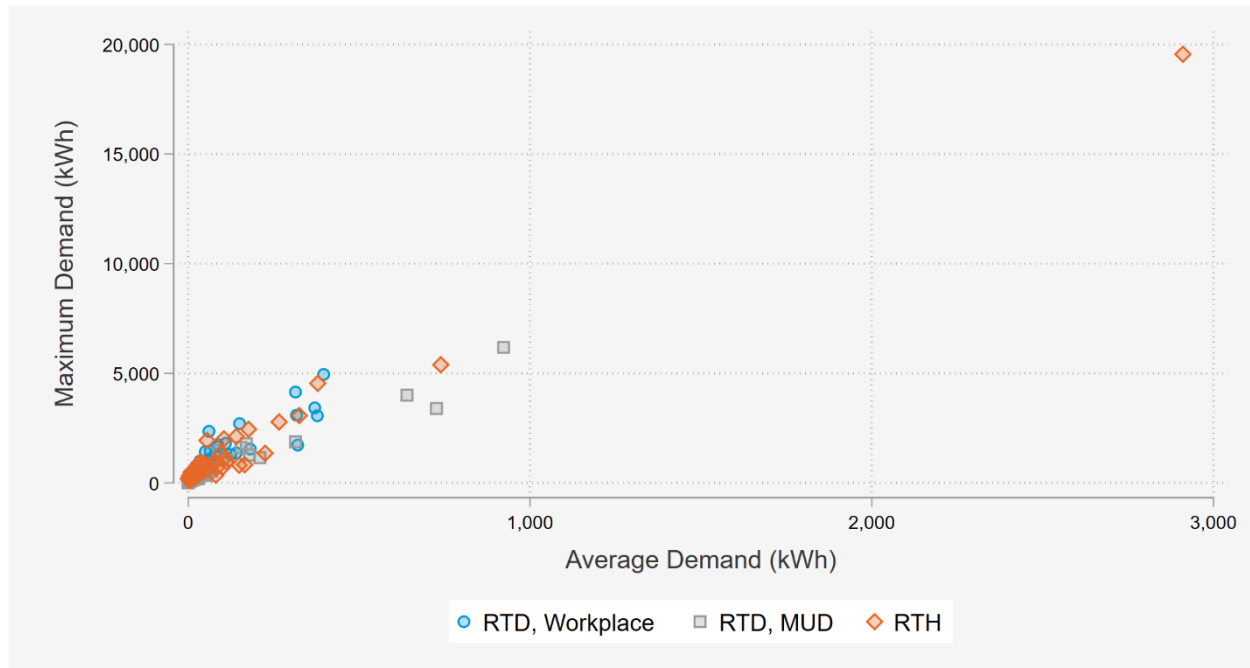
⁸ Some early program documentation for the Power Your Drive program at PG&E, SCE, and SDG&E suggested that rate-to-host sites had to plan to manage driver charging during events using a non-price mechanism or plan. These estimates, as well as conversations with program managers at SDG&E, suggest that is either not the case or the management has been ineffective. We have nevertheless included separate estimates for rate-to-host sites rather than including them explicitly as control sites.

Table 5: Estimated Elasticities (%) for PY 2022 -2025 Combined

	(1) Rate-to-Driver Workplace	(2) Rate-to-Driver MUD	(3) Rate-to-Host	(4) Rate-to-Host Omitted Site 1132
ln(Price)	-0.341*** (0.0538)	-0.283*** (0.0394)	0.129*** (0.0402)	-0.005 (0.0318)
Observations	3,222,188	2,769,091	1,745,116	1,710,063
Sites	92	79	51	50
Pseudo-R-Squared	0.7536	0.7664	0.8688	0.7427

Note: *** p<0.01, ** p<0.05, * p<0.1. This table reports coefficient estimates and standard errors from four separate Poisson regressions. All regressions are estimated using site-by-hour observations for October 1 2021 through September 30 2025. Standard errors are two-way clustered at the site and hour-of-sample level. Each specification includes fixed effects for site, date, day-of-week, weekend-by-hour-of-day, and temperature bin. Rate-to-host results in column (3) are reported for MUD and workplace combined because there is a single MUD site. Column (4) omits a large rate-to-host site that is an outlier in terms of maximum demand. Fixed effects in columns (3) and (4) are interacted with MUD/workplace status. All specifications include controls for event anticipation and rebound hours; we do not report coefficients on controls.

Figure 21: Site-Level Maximum Demand and Average Demand for Analysis Period



6.2 PRICE SENSITIVITY BY EVENT TYPE

We would like to understand whether customers are simply responding to the event adders, or they are also responsive to variation in the day-ahead wholesale price that is passed on. To do so, we can decompose the price response in our baseline price elasticity model into the price response attributable to local events, system events, and non-event hours. We report on results of this method in Table 6. This table reports coefficient estimates and standard errors from four separate Poisson regressions. The specification is identical to that in Equation 1 but we interact $\log(\text{Price})_{it}$ with four separate indicator variables representing hours when no events occurred, local events occurred, system events occurred, and both system events and local events occurred. The estimated coefficients reported in the first row indicate that customers are responsive to price even when no events are called. This holds true for both workplaces and MUDs. The caveat is that each of these price responses is identified from different sources of variation. Furthermore, for some event types, such as system events, there are only nine hours in the three year analysis period when a system event occurred and no local events occurred on any circuit (representing just 0.03% of observations).

Table 6: Estimated Elasticity (%) by Event Type

	(1) Rate-to-Driver Workplace	(2) Rate-to-Driver MUD	(3) Rate-to-Host	(4) Rate-to-Host Omitted Site 1132
ln(Price) x No Event	-0.347*** (0.0526)	-0.267*** (0.0492)	0.124*** (0.0420)	0.136*** (0.0404)
ln(Price) x Local Event	-0.350*** (0.0558)	-0.266*** (0.0478)	0.110** (0.0467)	0.138*** (0.0369)
ln(Price) x System Event	1.249** (0.574)	0.409 (0.370)	1.889*** (0.394)	1.203*** (0.288)
ln(Price) x Both Events	-0.485*** (0.154)	-0.778*** (0.175)	0.129** (0.0620)	0.106 (0.0816)
Observations	3,222,188	2,769,091	1,745,116	1,710,063
Sites	92	79	51	50
Pseudo-R-Squared	0.7536	0.7664	0.8688	0.7427

Note: *** p<0.01, ** p<0.05, * p<0.1. This table reports coefficient estimates and standard errors from three separate Poisson regressions. All regressions are estimated using site-by-hour observations for October 1 2021 through September 30 2025. Standard errors are two-way clustered at the site and hour-of-sample level. Estimated effects are at the site-level and include fixed effects for port, date, day-of-week, weekend-by-hour-of-day, and temperature bin. Rate-to-host results in column (3) are reported for MUD and workplace combined because there is a single MUD site. Column (4) omits a large rate-to-host site that is an outlier in terms of maximum demand. Fixed effects in columns (3) and (4) are interacted with MUD/workplace status. All specifications include controls for event anticipation and rebound hours; we do not report coefficients on controls.

6.3 LOAD IMPACTS ON HIGHEST SYSTEM LOAD DAYS

Although customers under at VGI sites 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 SDG&E delivers electricity to 3.7 million people in San Diego and southern Orange counties. It has 1.5 million residential and business accounts, a service area that 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.

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 VGI prices encourage customers to shift usage to lower-priced hours when the electric grid is not peaking. As Figure 5 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 22 shows the average hourly demand reduction from VGI sites in the 10 days when demand was highest for CAISO, CAISO net loads, and SDG&E. The change in peak and super-off-peak demand is similar for all three.

Table 7 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. For CAISO loads, the reductions were larger in magnitude on the top 5 and 10 highest system load days than on the top 20 highest system load days. Load reductions were similar across SDG&E top days.

Figure 22: Hourly Load Impacts on Top Highest Load Days by System

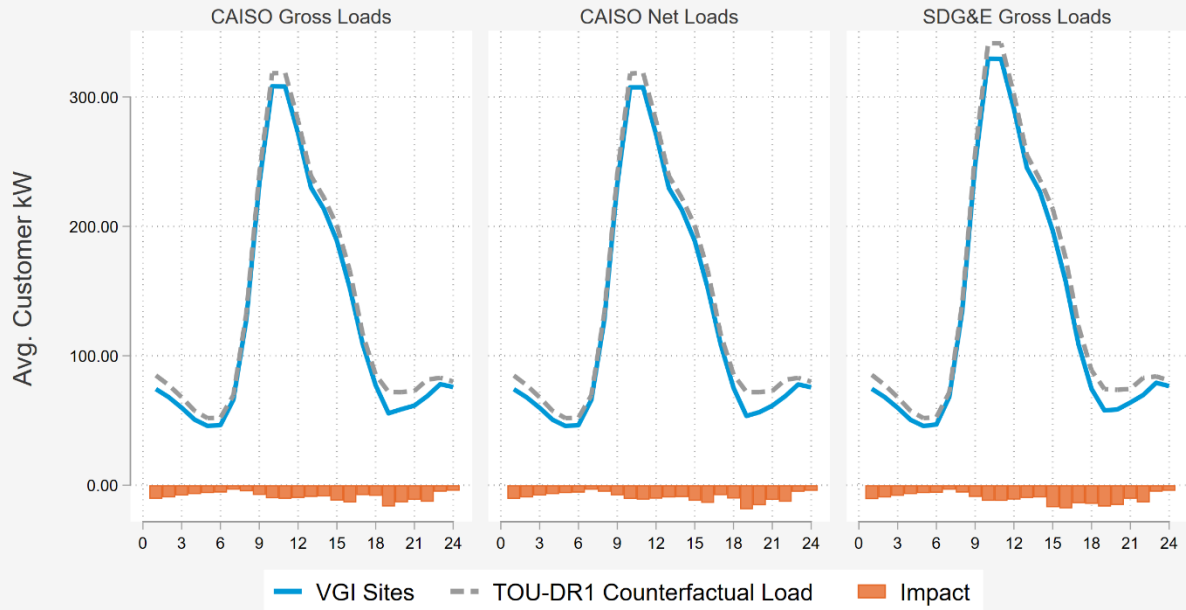


Table 7: Ex-post Demand Reductions on Highest System Load Days (4-9 PM)

System	Month	Total Sites	Daily avg. temp ^[2]	Avg. Customer (kW)			Load Impact (MW)
				Reference Load	Load Impact	% Change	
CAISO Gross Loads	Top 05 load day(s)	219	77.8	81.66	-16.40	-20.1%	-3.59
	Top 10 load day(s)	219	77.0	83.85	-11.35	-13.5%	-2.49
	Top 20 load day(s)	219	76.2	80.21	-8.23	-10.3%	-1.80
CAISO Net Loads	Top 05 load day(s)	219	77.8	81.66	-16.40	-20.1%	-3.59
	Top 10 load day(s)	219	76.7	83.79	-12.65	-15.1%	-2.77
	Top 20 load day(s)	221	75.9	80.14	-8.40	-10.5%	-1.86
SDG&E Gross Loads	Top 05 load day(s)	219	79.6	86.23	-14.67	-17.0%	-3.21
	Top 10 load day(s)	219	76.9	86.74	-14.09	-16.2%	-3.09
	Top 20 load day(s)	219	77.2	77.15	-10.01	-13.0%	-2.19

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

6.4 LOAD IMPACTS FOR MONTHLY WORST DAY

Figure 23 visualizes the hourly load impacts for the monthly worst day of each month. It shows the actual load for VGI sites and the reference load or counterfactual. The orange bars 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 23: Ex-post Monthly Worst Day (SDG&E) Hourly Load Impacts

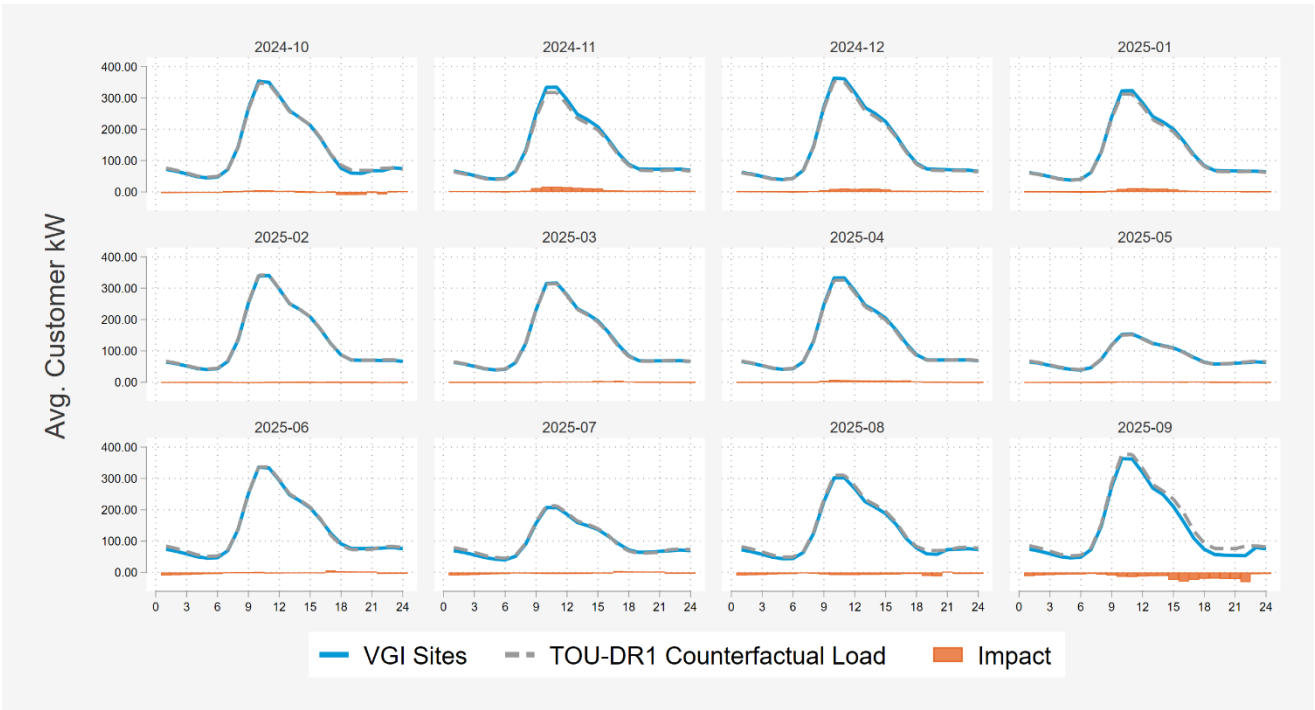


Table 8 summaries the hourly demand reductions for the worst days in each month. In general, estimating TOU impacts for a single hour is more difficult and noisier than estimating impacts for the average day of each month. Thus, we used to top 5 SDG&E load day for each month and also recommend a degree of caution in reviewing the monthly worst day impacts.

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

Hour Ending	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sep	Oct	Nov	Dec
1	0.97	-2.21	-1.34	-1.28	-2.27	-9.77	-9.82	-9.98	-11.18	-4.01	2.36	1.51
2	0.96	-1.89	-1.15	-1.08	-1.99	-8.75	-8.96	-8.83	-9.88	-3.39	2.34	1.47
3	0.87	-1.60	-0.97	-0.90	-1.66	-7.51	-7.76	-7.62	-8.43	-2.86	2.11	1.30
4	0.74	-1.34	-0.83	-0.75	-1.38	-6.22	-6.51	-6.41	-7.08	-2.40	1.78	1.10
5	0.55	-1.24	-0.75	-0.68	-1.27	-5.59	-5.69	-5.63	-6.39	-2.20	1.46	0.94
6	0.12	-1.37	-0.98	-0.92	-1.28	-5.18	-5.09	-5.18	-6.12	-2.27	1.03	0.48
7	0.36	-1.73	-1.20	-1.18	-1.04	-1.90	-2.82	-2.46	-4.07	0.66	1.69	0.89
8	0.80	-2.81	-1.98	-0.70	-0.43	-1.43	-3.02	-3.55	-6.51	1.21	4.13	2.14
9	4.30	-2.96	-1.41	3.97	0.87	-1.35	-3.89	-6.13	-10.32	4.28	12.21	5.86
10	9.55	-3.00	1.78	7.54	1.97	-0.89	-4.88	-7.93	-13.87	5.89	16.72	9.53
11	11.72	-1.13	1.60	6.63	2.04	-2.96	-5.27	-8.18	-14.26	5.13	16.80	10.32
12	11.18	-1.07	2.44	6.19	1.75	-2.85	-4.78	-8.35	-12.94	2.94	15.00	9.49
13	10.19	-0.82	2.57	5.33	1.42	-2.70	-4.41	-7.43	-11.39	3.63	12.93	10.02
14	10.19	-0.23	2.41	4.88	1.36	-2.49	-4.26	-7.33	-11.05	0.05	12.15	10.00
15	8.68	-0.46	3.77	5.50	1.41	-2.24	-2.81	-6.88	-23.38	-0.67	10.25	8.09
16	4.76	-1.54	2.98	4.43	0.93	-2.58	-3.02	-6.52	-29.53	-2.37	5.45	4.22
17	3.88	-0.07	4.36	5.71	2.14	5.96	4.61	-4.65	-23.37	-0.85	4.88	4.31
18	2.30	-0.51	2.74	2.84	1.40	4.33	3.57	-4.37	-19.65	-9.59	3.74	3.37
19	2.34	-0.52	0.98	0.91	0.18	3.62	3.00	-10.83	-19.18	-9.63	3.90	3.25
20	2.68	-0.38	0.81	0.72	-0.51	3.08	2.82	-11.87	-20.68	-9.34	4.23	3.57
21	2.77	-0.29	0.85	0.94	-0.33	3.19	3.15	2.48	-21.31	-0.88	4.26	3.63
22	0.88	-2.30	-1.18	-1.22	-1.95	-4.42	-3.90	-4.79	-30.42	-8.03	2.49	1.73
23	1.01	-2.11	-0.81	-1.12	-1.79	-3.96	-3.88	-4.68	-5.74	0.90	2.89	1.91
24	1.41	-1.72	-0.65	-0.95	-1.51	-3.64	-3.70	-4.01	-5.01	1.76	3.07	2.24

Demand Reductions are positive (Blue)

Load increases are negative (Orange)

6.5 LOAD IMPACTS FOR MONTHLY AVERAGE DAY

Figure 24 visualizes the hourly load impacts for the monthly average day of each month. It shows the actual load for sites on electric vehicle rates and the reference load or counterfactual. The orange bars 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.

Table 9 summarizes the hourly demand reductions for the average days in each month.

Figure 24: Ex-post Monthly Average Day Hourly Load Impacts

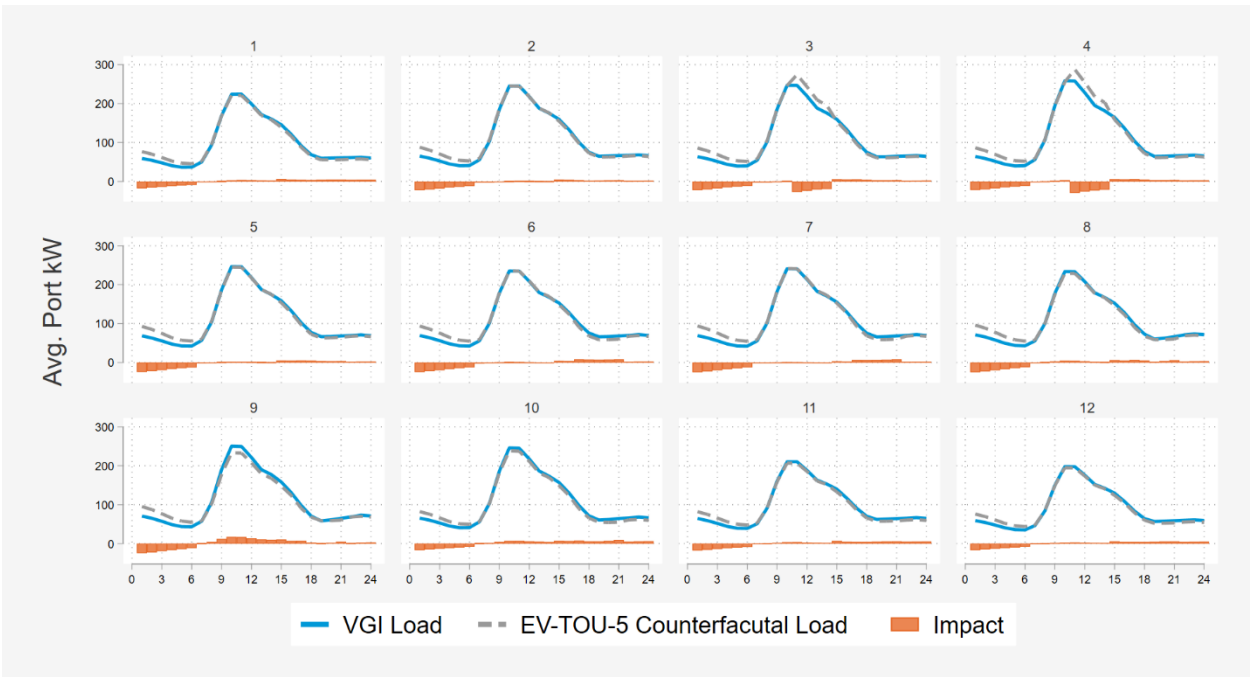


Table 9: Ex-post Monthly Average Day Hourly Demand Reductions per Site

Hour Ending	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sep	Oct	Nov	Dec
1	0.84	-1.91	-1.83	-1.33	-1.71	-9.20	-9.61	-9.84	-10.02	-3.79	2.06	1.65
2	0.91	-1.69	-1.54	-1.14	-1.43	-8.36	-8.69	-8.89	-9.00	-3.24	1.98	1.66
3	0.89	-1.44	-1.22	-0.90	-1.15	-7.24	-7.57	-7.68	-7.76	-2.74	1.80	1.54
4	0.77	-1.23	-1.02	-0.76	-0.93	-6.12	-6.40	-6.49	-6.58	-2.30	1.56	1.32
5	0.58	-1.20	-1.00	-0.70	-0.89	-5.45	-5.62	-5.72	-5.82	-2.08	1.26	1.07
6	0.24	-1.26	-1.16	-0.80	-0.96	-4.93	-5.09	-5.12	-5.34	-2.04	0.90	0.72
7	0.19	-1.57	-1.48	-0.99	-0.72	-2.64	-2.87	-3.10	-3.57	-0.06	1.21	0.92
8	0.42	-1.85	-1.76	-0.43	0.51	-2.29	-3.15	-3.67	-4.79	0.36	3.00	1.66
9	2.74	-0.02	0.21	3.07	2.90	-2.42	-4.25	-5.17	-5.74	3.67	8.05	4.45
10	6.39	2.05	3.40	5.71	4.33	-2.48	-5.18	-6.56	-7.29	6.63	11.11	6.77
11	8.19	3.74	3.84	5.24	4.31	-3.02	-5.36	-6.76	-7.51	7.05	11.52	7.48
12	7.90	3.80	4.44	5.07	3.98	-2.73	-4.85	-6.48	-7.12	6.19	10.59	6.97
13	7.45	3.60	4.38	4.59	3.49	-2.62	-4.38	-6.09	-6.50	5.30	9.58	6.53
14	7.64	3.60	4.32	4.38	3.37	-2.49	-4.26	-6.08	-6.26	4.25	9.18	6.27
15	6.79	3.44	5.04	5.12	3.18	-0.84	-2.90	-4.54	-7.01	4.72	8.11	5.32
16	4.05	2.11	4.26	4.28	2.69	-0.95	-2.90	-4.43	-7.31	3.35	4.02	2.97
17	3.14	1.18	4.71	5.53	4.30	6.32	4.82	1.87	-0.37	6.90	3.80	3.32
18	2.07	-0.23	2.20	3.56	2.81	4.75	3.64	0.24	-3.53	3.23	3.12	2.68
19	2.26	-0.29	0.44	1.00	1.00	3.70	3.14	-3.74	-6.24	2.43	3.19	2.86
20	2.59	-0.03	0.22	0.72	0.32	3.24	3.01	-2.04	-3.85	3.65	3.44	3.17
21	2.76	0.06	0.34	0.83	0.39	3.31	3.24	0.23	-1.54	5.51	3.60	3.29
22	1.05	-1.94	-1.62	-1.04	-1.55	-3.57	-3.81	-4.11	-6.62	-0.02	1.88	1.63
23	1.28	-1.73	-1.46	-0.95	-1.30	-3.31	-3.65	-3.94	-4.17	1.12	2.13	1.85
24	1.46	-1.42	-1.25	-0.80	-1.16	-3.14	-3.47	-3.53	-3.85	1.54	2.42	2.00

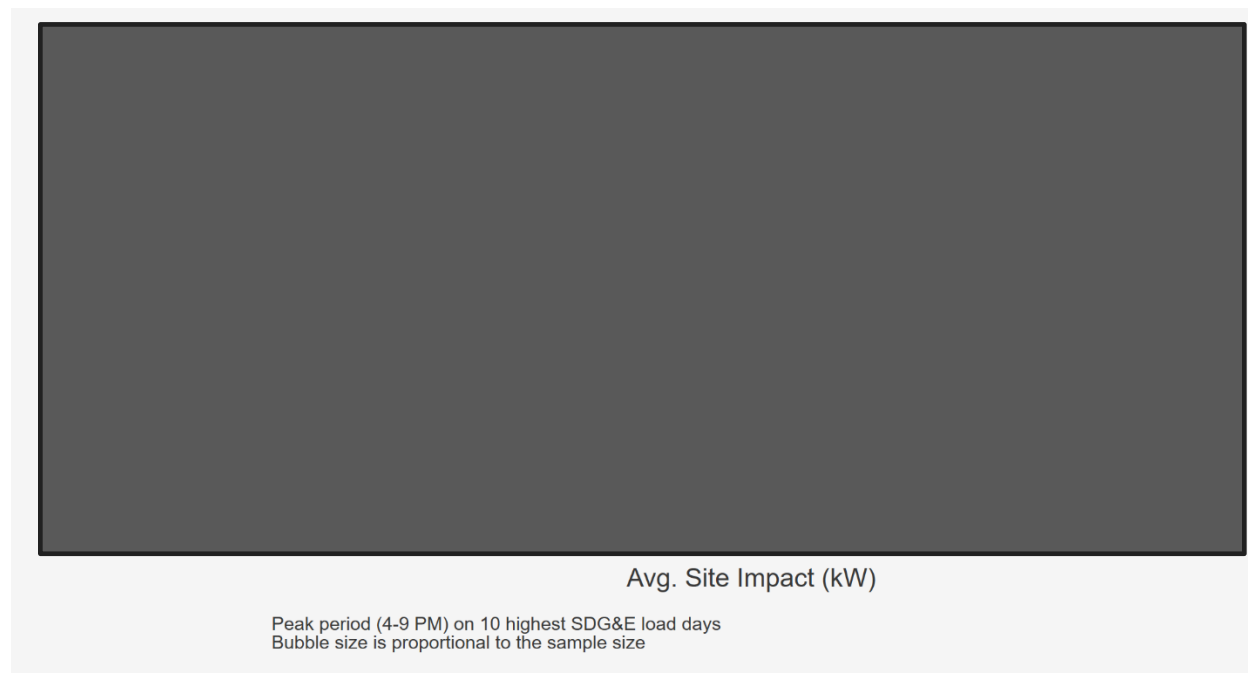
Demand Reductions are positive (Blue)

Load increases are negative (Orange)

Load Impacts by Customer Type

Figure 25 shows the impacts of key customer segments for the peak period (4-9PM) on the ten highest SDG&E system load days. The results across categories should be interpreted as descriptive, not causal. We caution that results are noisier when the estimating sample size is smaller such as for the RTH since MUD has only one site.

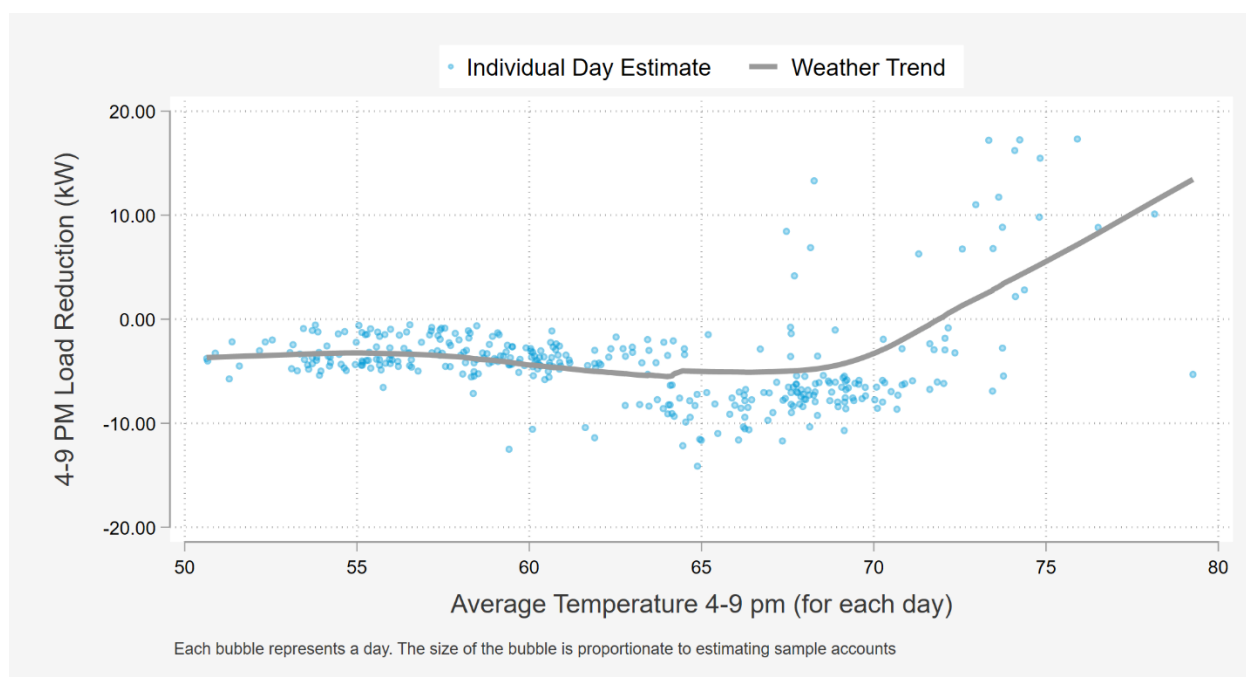
Figure 25: Load Impacts per Site for Key Customer Segments



6.6 WEATHER SENSITIVITY OF LOAD IMPACTS

A key question for time varying residential rates is whether the peak period load impacts are weather sensitive. While the electric vehicle rates are designed to encourage charging during super off-peak hours, the rates reflect the real time whole sale price plus per site adders. 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 price elasticity modeling. Figure 26 shows the relationship between the daily peak period (4-9) load impacts and weather for customers already being charged VGI rates for their electric vehicles. In general, the demand reductions grow larger when temperatures are hotter, and more so at higher temperatures. Customers have an incentive to shift non-EV loads because the rates apply to the whole home, not just the electric vehicle.

Figure 26: Peak Period (4-9 PM) Demand Reduction Weather Sensitivity



7 VEHICLE GRID INTEGRATION EX-ANTE RESULTS

7.1 OVERALL RESULTS

Figure 27 shows a heat map of the per-customer load reduction by month and hour of day for SDG&E 1-in-2 monthly peak day weather conditions. The results are scaled to reflect the current mix of sites on electric vehicle VGI rates (versus the available estimating sample). Table 10 and Table 11 show the per-customer hourly impacts for each month under CAISO and SDG&E monthly peaking conditions, respectively. The tables are designed to enable the CPUC's Slice-of-Day Resource Adequacy requirements. The estimated reductions are greater on monthly worst days than on average weekdays and reductions are greater in hotter months than in cooler ones. The load reductions also coincide with the hours (4-9 PM) and months (August and September) when reductions are needed most.

Figure 27: Heat map of Per Customer Ex-Ante Demand Reductions by Hour and Month

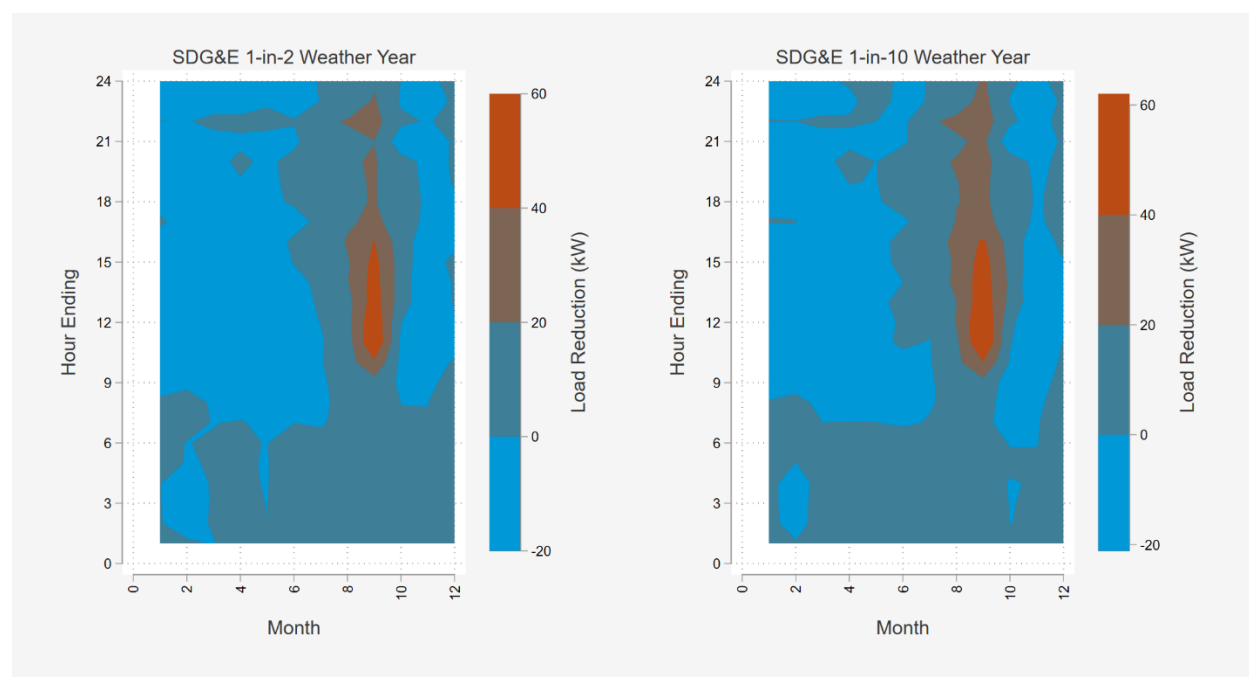


Table 10: Slice of Day Table for CAISO 1-in-2 Weather Year Monthly Worst Day (Per Customer Demand Reductions)

Hour Ending	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sep	Oct	Nov	Dec
1	0.85	0.81	-0.53	1.38	0.00	6.49	7.56	11.00	15.68	4.67	-0.52	5.27
2	0.66	0.41	0.19	0.41	0.49	5.59	5.83	9.22	7.99	1.45	0.38	4.53
3	0.51	0.41	0.20	0.17	0.19	4.77	4.88	7.90	6.77	1.87	0.03	3.87
4	0.42	0.30	0.12	0.02	0.03	3.89	3.85	6.41	5.44	-0.77	-0.21	3.17
5	0.44	0.50	-0.08	-0.11	-0.10	3.59	3.29	5.79	4.78	-0.30	0.13	2.93
6	0.67	0.91	-0.06	-0.15	-0.04	3.39	2.88	5.72	4.45	1.01	-0.71	3.13
7	0.75	1.26	-1.11	-1.18	-0.64	-0.69	-0.50	4.21	2.48	-4.04	-1.61	4.71
8	1.63	0.98	-2.58	-2.82	-1.19	-2.33	-1.27	4.04	4.55	-6.22	-4.52	9.02
9	0.34	-1.95	-9.40	-9.62	2.24	-6.05	-3.36	10.87	10.07	-11.01	-13.04	12.71
10	-1.44	-9.20	-19.79	-15.46	2.02	-5.26	-5.95	18.79	27.06	-2.56	-20.45	13.17
11	-7.62	-16.77	-21.50	-15.09	2.76	-1.16	-11.00	20.17	37.82	-3.23	-22.60	6.60
12	-10.84	-18.83	-20.74	-15.04	2.41	-1.28	-9.18	21.97	37.55	-0.09	-22.36	-1.46
13	-10.48	-17.63	-18.15	-13.59	0.83	3.08	-7.50	22.01	33.71	7.20	-19.96	-5.96
14	-12.24	-18.11	-15.61	-7.33	0.34	-4.65	-2.57	28.33	31.80	10.05	-18.01	-12.70
15	-10.95	-15.13	-16.25	-3.66	0.66	-0.25	-2.00	27.25	31.12	9.92	-16.66	-8.59
16	-8.45	-12.24	-13.70	-4.24	-0.38	-2.06	-2.04	26.19	28.20	5.00	-13.69	-0.43
17	-0.09	-2.07	-8.70	-4.14	-3.09	-4.66	2.73	18.18	18.94	12.13	-7.38	7.17
18	-1.16	-2.21	-7.27	-2.94	-2.06	3.35	10.68	18.93	19.08	10.59	-4.27	5.84
19	-2.91	-2.72	-6.43	1.30	0.06	3.95	13.92	21.45	20.78	8.63	-4.24	4.29
20	-5.44	-6.21	-5.79	5.56	0.69	5.72	15.03	24.08	22.75	5.07	-9.19	3.60
21	-2.97	-1.96	-8.48	-1.10	-0.15	0.15	11.33	20.56	22.57	-8.76	-10.91	6.27
22	-1.75	-1.36	-5.72	-1.11	1.87	-3.49	15.27	24.24	27.20	0.98	-8.63	7.39
23	-3.82	-5.57	-8.89	-9.32	9.98	-9.48	-4.41	20.17	23.57	-5.93	-9.97	4.87
24	-1.15	-2.03	-1.64	0.34	6.25	-3.78	-1.65	2.59	19.50	-2.85	-1.81	5.09

Demand Reductions are positive (Blue)

Load increase are negative (Orange)

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

Hour Ending	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sep	Oct	Nov	Dec
1	0.64	0.21	0.85	3.23	8.40	4.70	6.48	8.08	16.80	3.08	1.08	3.25
2	0.60	-0.89	1.14	1.41	1.58	4.80	6.05	6.68	8.17	-0.15	1.38	3.02
3	0.42	-0.75	0.86	1.23	1.28	4.29	5.31	5.52	6.76	-0.29	1.03	2.61
4	0.41	-0.72	0.66	1.07	0.91	3.90	4.43	4.47	5.55	-0.71	0.94	2.14
5	0.51	-0.01	0.33	0.54	0.61	3.31	3.71	4.03	4.94	1.91	0.69	1.86
6	0.59	0.12	0.44	0.44	0.60	3.25	3.21	3.66	4.96	-0.51	-0.19	2.19
7	0.27	0.39	0.02	0.17	0.09	-0.71	0.37	2.22	3.22	-5.26	-0.34	3.14
8	0.40	0.96	-0.84	-1.64	-1.31	-3.21	-0.44	1.92	6.41	-7.33	-2.43	5.95
9	-2.34	-1.15	-2.88	-9.14	-4.09	-6.96	-1.06	4.80	14.10	-9.58	-9.03	7.95
10	-4.40	-5.43	-9.84	-15.09	-5.04	-4.73	-1.23	15.05	39.50	-1.57	-16.26	4.31
11	-6.91	-9.21	-21.15	-15.00	-3.76	2.32	-0.60	15.87	62.04	1.67	-19.63	1.12
12	-10.46	-9.32	-20.43	-13.24	-6.16	2.21	1.69	20.96	60.99	4.72	-18.27	-2.23
13	-10.73	-10.21	-17.78	-12.05	-5.92	7.10	3.71	19.80	53.45	14.68	-15.37	-6.85
14	-11.83	-12.84	-15.50	-6.14	-7.22	-0.22	4.36	24.96	50.31	16.17	-17.77	-6.04
15	-6.61	-7.36	-15.60	-2.42	-7.27	5.77	5.52	23.15	48.68	14.58	-14.77	-0.34
16	-2.57	-2.62	-12.65	-2.55	-6.13	5.82	6.51	26.68	42.94	12.12	-12.03	5.48
17	0.23	0.28	-7.50	-1.58	-3.33	-2.22	6.41	20.78	25.93	11.62	-3.81	8.76
18	-0.81	-1.91	-5.94	-1.96	-1.53	5.78	12.47	19.56	22.89	11.23	-1.80	6.09
19	-2.10	-2.39	-5.36	0.36	-0.37	6.85	14.23	19.69	23.56	9.69	-2.19	3.90
20	-2.50	-2.97	-5.01	5.99	-0.27	9.20	16.19	21.17	25.47	8.45	-4.12	3.78
21	-5.18	-5.05	-4.02	-3.80	-4.16	-2.50	12.52	16.69	24.31	-12.20	-10.78	3.03
22	0.30	0.12	2.19	1.75	0.07	-3.65	17.78	24.28	30.74	3.25	-7.47	6.45
23	-2.55	-3.61	-4.89	-3.46	6.72	-5.32	1.21	10.69	26.04	-0.46	-9.12	2.76
24	-1.22	-2.17	-2.38	1.73	7.58	-4.14	0.81	3.70	22.85	1.15	-2.34	3.18

Demand Reductions are positive (Blue)

Load increase are negative (Orange)

Figure 28 and Figure 29 show the estimated ex-ante load profiles for sites on electric vehicle VGI rates. Both figures show profiles for the August worst day, and both figures use SDG&E weather conditions rather than CAISO conditions. Figure 28 shows profiles under 1-in-2 weather conditions, and shows profiles for 1-in-10. Note that the forecast year shown is 2025.

Figure 28: Aggregate Ex-ante Impact for 1-in-2 Weather Conditions, September Worst Day 2026

San Diego Gas & Electric
PY2025 EV VGI Rates Ex Ante Impacts

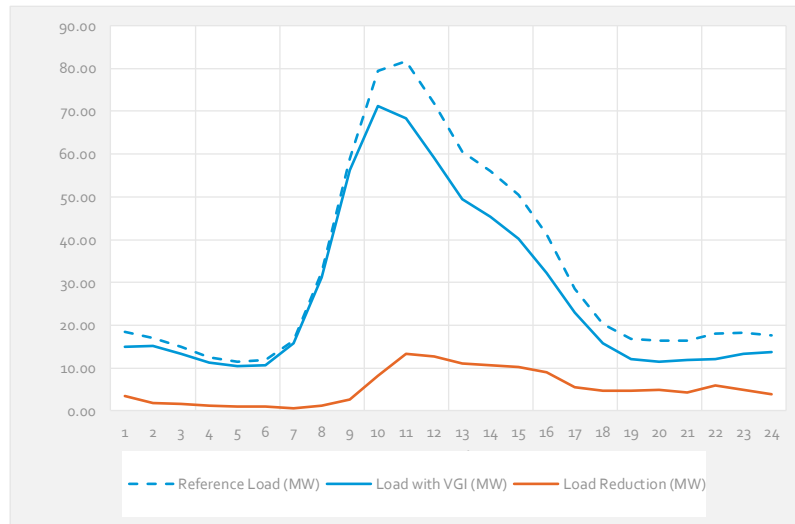


Table 1: Menu options

Rate Type	All
Type of Result	Aggregate Total
System (CAISO/SDG&E)	SDG&E
Weather Year	1-IN-2
Forecast Year	2025
Category	All
Subcategory	All
Day type	MONTHLY SYSTEM WORST DAY
Month	09 Sep
Hour Ending View	HE (Prevailing Time)

Table 2: Event day information

Total sites	222
Daily Max Temp	92.2
Peak Period (4pm-9pm) Impact (MW)	4.84
Peak Period (4pm-9pm) Impact (%)	24.6%



Hour Ending	Reference Load (MW)	Load with VGI (MW)	Load Reduction (MW)	% Load Reduction	Avg Temp (°F, Site-Weighted)	Uncertainty Adjusted Impact -		Standard Error	T-Statistic
						5th	95th		
1	18.55	15.07	3.48	18.8%	73.86	2.03	4.93	0.88	3.95
2	16.99	15.15	1.83	10.8%	73.50	1.09	2.58	0.45	4.04
3	14.90	13.37	1.53	10.3%	72.55	0.90	2.16	0.38	4.01
4	12.60	11.34	1.26	10.0%	71.71	0.75	1.76	0.31	4.08
5	11.48	10.37	1.11	9.7%	71.49	0.71	1.51	0.24	4.58
6	11.82	10.70	1.11	9.4%	71.34	0.77	1.45	0.21	5.41
7	16.44	15.78	0.67	4.1%	71.11	0.37	0.96	0.18	3.70
8	32.41	31.26	1.15	3.5%	71.33	0.57	1.73	0.35	3.25
9	58.95	56.20	2.75	4.7%	76.16	1.54	3.96	0.74	3.74
10	79.33	71.19	8.14	10.3%	81.83	5.45	10.82	1.63	4.99
11	81.67	68.40	13.27	16.2%	87.18	9.13	17.40	2.52	5.27
12	71.79	59.04	12.75	17.8%	90.85	8.95	16.56	2.31	5.51
13	60.56	49.45	11.11	18.3%	91.07	7.90	14.33	1.95	5.69
14	55.99	45.31	10.68	19.1%	92.03	7.70	13.66	1.81	5.89
15	50.43	40.24	10.19	20.2%	92.16	7.42	12.95	1.68	6.06
16	41.26	32.17	9.09	22.0%	92.07	6.69	11.49	1.46	6.24
17	28.53	22.96	5.57	19.5%	91.78	4.11	7.04	0.89	6.26
18	20.41	15.72	4.69	23.0%	90.50	3.31	6.07	0.84	5.59
19	16.78	12.06	4.72	28.1%	87.22	3.16	6.29	0.95	4.96
20	16.33	11.51	4.82	29.5%	83.35	3.19	6.46	0.99	4.85
21	16.36	12.00	4.37	26.7%	79.89	2.83	5.91	0.94	4.66
22	18.08	12.07	6.00	33.2%	78.60	3.76	8.24	1.36	4.40
23	18.23	13.33	4.90	26.9%	76.92	3.01	6.80	1.15	4.27
24	17.68	13.79	3.89	22.0%	75.05	2.31	5.47	0.96	4.04
Daily	MWh	MWh	MWh	% Change	Avg Temp (°F, Site-Weighted)	Uncertainty Adjusted Impact - Percentiles		Std Err	T-statistic
						5th	95th		
Overall	787.57	658.48	129.09	16.4%	81.0	127.06	131.13	1.24	104.26
Peak Hours	98.42	74.24	24.18	24.6%	86.5	22.66	25.70	0.92	26.16

Figure 29: Aggregate Ex-ante Impact for 1-in-10 Weather Conditions, September Worst Day 2026

San Diego Gas & Electric
PY2025 EV VGI Rates Ex Ante Impacts

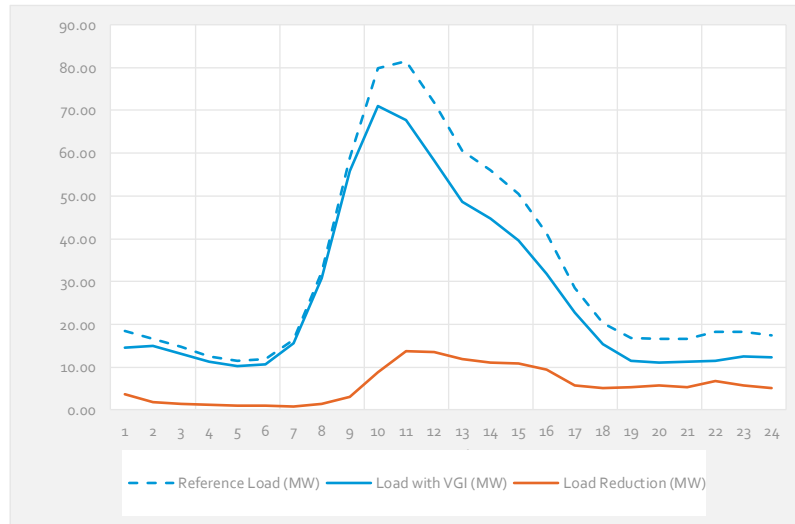


Table 1: Menu options

Rate Type	All
Type of Result	Aggregate Total
System (CAISO/SDG&E)	SDG&E
Weather Year	1-IN-10
Forecast Year	2025
Category	All
Subcategory	All
Day type	MONTHLY SYSTEM WORST DAY
Month	09 Sep
Hour Ending View	HE (Prevailing Time)

Table 2: Event day information

Total sites	222
Daily Max Temp	95.6
Peak Period (4pm-9pm) Impact (MW)	5.42
Peak Period (4pm-9pm) Impact (%)	27.4%



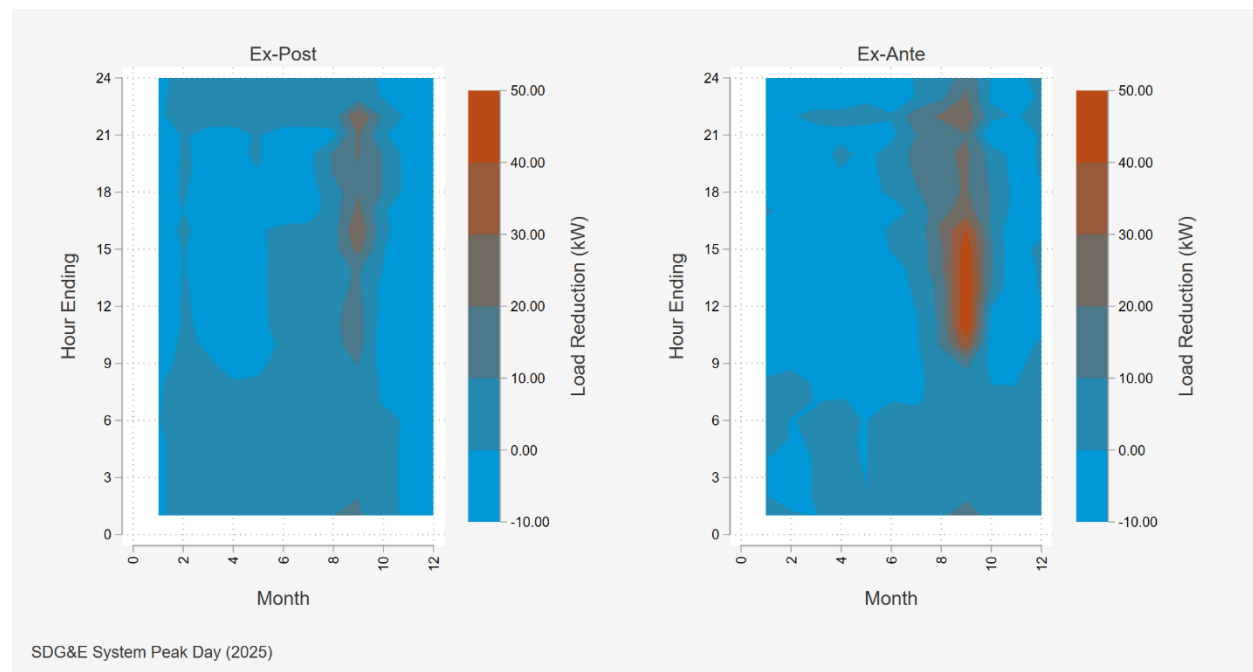
Hour Ending	Reference Load (MW)	Load with VGI (MW)	Load Reduction (MW)	% Load Reduction	Avg Temp (°F, Site-Weighted)	Uncertainty Adjusted Impact -		Standard Error	T-Statistic
						5th	95th		
1	18.38	14.65	3.73	20.3%	75.41	2.15	5.31	0.96	3.88
2	16.70	14.89	1.81	10.9%	74.85	1.08	2.55	0.45	4.07
3	14.72	13.22	1.50	10.2%	73.65	0.89	2.11	0.37	4.04
4	12.45	11.22	1.23	9.9%	72.65	0.74	1.72	0.30	4.14
5	11.43	10.33	1.10	9.6%	73.30	0.70	1.49	0.24	4.55
6	11.82	10.71	1.10	9.3%	72.85	0.76	1.44	0.21	5.33
7	16.41	15.69	0.72	4.4%	73.01	0.38	1.05	0.20	3.52
8	32.23	30.80	1.42	4.4%	73.89	0.69	2.16	0.45	3.18
9	58.95	55.82	3.13	5.3%	77.62	1.73	4.54	0.85	3.67
10	79.87	71.11	8.77	11.0%	82.54	5.96	11.58	1.71	5.14
11	81.58	67.80	13.77	16.9%	88.60	9.53	18.01	2.58	5.34
12	71.79	58.25	13.54	18.9%	93.67	9.52	17.57	2.45	5.53
13	60.56	48.69	11.87	19.6%	94.38	8.47	15.26	2.06	5.75
14	55.99	44.82	11.17	19.9%	94.05	8.06	14.28	1.89	5.91
15	50.43	39.62	10.81	21.4%	95.58	7.88	13.73	1.78	6.07
16	41.26	31.73	9.53	23.1%	95.08	7.03	12.03	1.52	6.27
17	28.53	22.78	5.76	20.2%	93.02	4.24	7.27	0.92	6.24
18	20.41	15.33	5.08	24.9%	94.69	3.58	6.58	0.91	5.58
19	16.78	11.55	5.23	31.2%	92.67	3.47	6.99	1.07	4.88
20	16.63	10.98	5.65	34.0%	89.73	3.76	7.55	1.15	4.90
21	16.65	11.25	5.40	32.4%	87.50	3.54	7.26	1.13	4.78
22	18.30	11.48	6.82	37.3%	83.94	4.28	9.37	1.55	4.41
23	18.26	12.48	5.78	31.7%	81.90	3.53	8.03	1.37	4.23
24	17.46	12.38	5.07	29.1%	81.78	2.97	7.17	1.28	3.97
Daily	MWh	MWh	MWh	% Change	Avg Temp (°F, Site-Weighted) F	Uncertainty Adjusted Impact - Percentiles		Std Err	T-statistic
						5th	95th		
Overall	787.60	647.59	140.00	17.8%	84.0	137.81	142.19	1.33	105.09
Peak Hours	99.00	71.89	27.12	27.4%	91.5	25.40	28.83	1.04	26.01

7.2 EX-POST TO EX-ANTE COMPARISON

When comparing ex-post and ex-ante, it is important to keep the distinction between the two estimates in mind. Ex-ante impacts are estimates of the future resources available under standardized planning conditions (defined by weather). Ex-post impacts are estimates of what past impacts were given the weather, conditions, and magnitude of resources available. The ex-ante impacts are based on the ex-post impact and weather trends, as shown earlier in Figure 26.

Figure 30 compares the per site ex-post load impacts to the ex-ante load impacts for the average weekday by month and hour. The ex-post load impacts are very similar in magnitude to the ex-ante impact estimates shown in the table. Both have the highest reductions in the Fall, though for ex-post this peak occurs slightly earlier. Ex-ante has higher sustained reductions through all months in peak hours. The differences are due to weather and composition of the samples. The ex-ante standardized weather indicates hotter weather conditions typically occur in August in September, and this is reflected in higher impacts in those months.

Figure 30: Comparison of Ex-Post and Ex-Ante Per Customer Demand Reductions under SDG&E Peak Conditions (2025)



8 RECOMMENDATIONS

Electric vehicles have the potential to fundamentally transform the electric grid. They are a new, incremental, flexible, and critical load. As the residential electric vehicle market grows, it will impact all aspects of the electric grid. The efforts to ensure electric vehicles are a flexible load over the next few years will be vital as the market share increases. There are over 2.9M vehicles in SDG&E territory and the implications of transportation electrification for the electric grid are large. Moreover, electric vehicles are quickly maturing from an early adopter technology to mass adoption. The transformation is most evident for new vehicles, where electric vehicles constitute 24% of new sales in San Diego County. Thus, it has become increasingly important to provide customers incentives and tools to manage charging to lower bills and reduce use during peak hours.

The key recommendations from the evaluation are:

- **Local events should be called in future program years.** In this program year, a change in to the event forecasting algorithm meant no local events were called. That should be corrected such that more local events are called in future program years. In a very mild year, local events might not be economically efficient, but they still have value for EM&V purposes. In this evaluation, they represent the best-available source of variation to estimate price responsiveness.
- **Access the PYD charging application data to examine customer engagement and price threshold settings.** In the application, customers have the ability to set a price threshold to automate the charging response at PYD sites. We recommend accessing these data for use in future evaluations. Firstly, they can be used to assess customer engagement with this feature and the program in general. Application usage and thresholds data may also allow us to identify when a customer has intended to charge, seen a price, and chosen not to charge, instead of only identifying times when a customer has chosen to charge.
- **Future analysis could report more robustness checks and alternative specifications.** The event impacts estimated in this study incorporate any effect of higher day-ahead wholesale prices during event hours. An alternative specification could control for the day-ahead hourly price in the event response model. Alternative approaches could include saturated fixed effects at the port and hour-of-sample level, which would preclude identifying system events. Other specifications could include driver-level fixed effects to control for unobserved heterogeneity across drivers.
- **Future analysis could examine more heterogeneous effects.** While MUD sites might be fairly homogeneous, workplace sites could be categorized using NAICS code or other information so effects could be examined across business types. This program year we attempted to use NAICS code but the data were missing for too many sites. Since there are fewer than 100 workplace sites, we could attempt to categorize the sites “by hand” using the site address and maps. In PY2025, limited local events meant that the value of including additional robustness checks and heterogeneous effects was limited. In future program years with more events, these effects should be investigated.

SDG&E's VGI rate is innovative because it reflects hourly day-head market prices and incorporates system and local peaking conditions adders. It provides a potential model for upcoming real-time pricing pilots in California. The findings also imply that electric vehicle loads are more price-responsive than typical household loads. Thus, while the VGI rate is limited to Level 2 chargers, it has significant policy implications. While dynamic rates are considered a passive form of load management, they are effective and lead to changes in charging patterns. SDG&E should continue to work towards enrolling customers onto time-varying rates. In addition, SDG&E may want to consider including Level 3 charges (DCFC fast chargers) in the PYD program, especially as fleets become more common. Level 2 chargers generally have low utilization and are not destination chargers due to the longer charge times.

9 APPENDIX: EVENT-BASED RESULTS

Table 12 shows estimated average site-level impacts in response to events. At rate-to-driver sites where drivers pay for charging, we find that drivers reduced their energy use when prices were higher. The reductions are generally statistically significant at the 1% level, and large in both kW and relative (%) terms. Local circuit event impacts are typically larger than system event impacts, because local events tend to be called during hours where circuits normally have higher loads. At rate-to-host sites, where the host pays and charging is free at the port for the driver, we find little evidence of load impacts during events.

Table 12: Event Response Estimates Summary

Sector	Sites	Local Event Impact (kW)	System Event Impact (kW)	Local Event Impact (%)	System Event Impact (%)
Rate-to-Driver Workplace	92	-34.26***	-10.66**	-0.605***	-0.476***
Rate-to-Driver MUD	79	-18.35**	-20.57**	-0.548***	-0.334***
Rate-to-Host	51	-36.73	59.82	0.277***	0.301***

Note: *** p<0.01, ** p<0.05, * p<0.1. Negative coefficients represent load reductions. Over the 4-year analysis period, local events were called on 601 days, and system events were called on 125 days.

9.1 EMPIRICAL MODEL: EVENT RESPONSE

To recover the causal effect of system- and local-events on charging demand, DSA estimated impacts using a panel regression with multiple fixed effects. We estimate both level effects (in terms of kW reductions) and relative effects (in terms of % reductions). A counterfactual estimate of a charging demand during system events is developed using average non-event load on other days after controlling for observables and during local events using both average non-event load on other days and average load for sites not subject to events.

LEVELS EFFECTS (kW)

Equation 2 specifies the event response model used to produce site-level impacts in kW. The model is estimated by OLS regression on data at the individual site i , hourly date-time t level spanning October 1 2021 to September 30 2024.

Equation 2: Event Response OLS Model Specification

$$kW_{it} = \beta_1 \text{System Event}_t + \beta_2 \text{Local Event}_{it} + \beta_3 \text{System Event}_t \times \text{Local Event}_{it} + \beta_4 A_{it} + \beta_5 R_{it} + \rho_{site} + \delta_{date} + \omega_{dow} + \tau_{temp} + \pi_{hour} + \varepsilon_{it}$$

Table 13 defines each model term in the equations above.

Table 13: Description of Model Terms

Model Term	Description
kW_{it}	kW for site i at time t
System Event_t	Variable encoding a system event occurring at time t
Local Event_{it}	Variable encoding a distribution circuit event occurring at time t on site i
A_{it}	Control variable for an anticipation hour, encoded as the 24 hours preceding the first event hour
R_{it}	Control variable for a rebound hour, encoded as the 24 hours following the last event hour
ρ_{site}	site fixed effect
δ_{date}	Date fixed effect
ω_{dow}	Day of week fixed effect
τ_{temp}	Hourly temperature bin fixed effect
π_{hour}	Hour by weekend/weekday fixed effect
ε_{it}	Error term

The coefficients of interest are β_1 , the average effect of a system event on load, and β_2 , the average effect of a local event on load. We control for anticipation hours and rebound hours, to account for drivers charging more in anticipation of higher event prices and any rebound effect following reduced charging during events. We include site-level fixed effects to control for unobservable features of a site that are constant over time, for example, if drivers at a workplace commute from a long distance or a site is inconveniently located and not used. Date-level fixed effects control for variables that affect demand that are common across sites, for example, changes in the availability or prices of substitute charging stations in the SDG&E territory. Day-of-week effects control for variation in charging due to intra-week patterns such as no workplace charging on weekends or higher charging on Mondays. Temperature bin fixed effects control for any effect of hourly temperature on charging. For example, lower or higher efficiency that occurs at different temperature ranges.⁹ We finally include hour-by-weekend/weekday fixed effects to control for hourly variation in load that differs by weekend/weekday.

We estimate the model separately for rate-to-driver workplace sites, rate-to-driver MUD sites, and rate-to-host sites. Standard errors are two-way clustered at the site, hour-of-sample level. Rate-to-host site results are pooled for workplaces and MUDs because there is a single MUD site, so effects cannot be separately estimated for rate-to-host MUD sites with valid inference because there is only a single

⁹ Temperature is split into bins using the following cut points: (25, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 105). High and low temperatures have wider bins to ensure at least 1% of observations fall in each bin.

site. For rate-to-host sites, we interact all fixed effects apart from temperature with MUD/workplace status.

RELATIVE EFFECTS (%)

To recover relative impacts in percent terms, we model kW_{it} as a Poisson random variable with parameter $\lambda_{it} > 0$. We model λ_{it} as an exponential function of the covariates in the linear model above (excluding the error term):

Equation 3: Event Response Model Poisson Specification

$$\lambda_{it} = e^{X'_{it}\theta},$$

where,

$$X'_{it}\theta = \beta_1 \text{System Event}_t + \beta_2 \text{Local Event}_{it} + \beta_3 \text{System Event}_t \times \text{Local Event}_{it} + \beta_4 A_{it} \\ + \beta_5 R_{it} + \rho_{site} + \delta_{date} + \omega_{dow} + \tau_{temp} + \pi_{hour}.$$

Just as for the level effects model, the model is estimated on data at the individual site i , hourly date-time t level spanning October 1 2021 to September 30 2024. We estimate the model separately for rate-to-driver workplace sites, rate-to-driver MUD sites, and rate-to-host sites. Standard errors are two-way clustered at the site, hour-of-sample level.

9.2 LOAD IMPACTS OF SYSTEM AND DISTRIBUTION ADDERS

Table 14 presents local- and system-event impacts in kW for the average site for each site type. The table includes coefficient estimates and standard errors from three separate OLS regressions: rate-to-driver, workplace estimates are presented in column (1); rate-to-driver, MUD estimates are presented in column (2); and rate-to-host estimates are presented in column (3). These estimates pool data from program years 2022 through 2024. Program year 2024 estimates are presented in the Appendix. On average, sites at rate-to-driver workplace sites delivered load reductions of 34.26 kW during local event hours and 10.66 kW during system event hours. On average, sites at rate-to-driver MUD sites delivered load reductions of 18.35 kW during local event hours and 20.57 kW during system event hours. These impacts are large and statistically significant at the 10% level, save for the workplace system impacts, which are statistically significant at the 1% level. Local event load reductions are larger than system event load reductions, because local events tend to be called in hours with more charging load. For workplaces, there is evidence that reductions are not additive when local and system events are called together.

Column (3) reports estimates for rate-to-host sites where charging is free at the sites for drivers and the VGI rate is paid by the site host. We find the estimated impacts for rate-to-host sites are statistically indistinguishable from zero. This serves as a check on our main specification. If we were to find statistically significant reductions or increases in load at rate-to-host sites, where there is no reason to

expect drivers to respond to price¹⁰, we would be concerned that our estimates for rate-to-driver sites were biased.

¹⁰ Some early program documentation for the Power Your Drive program at PG&E, SCE, and SDG&E suggested that rate-to-host sites had to plan to manage driver charging during events using a non-price mechanism or plan. These estimates, as well as conversations with program managers at SDG&E, suggest that is either not the case or the management has been ineffective. We have nevertheless included separate estimates for rate-to-host sites rather than including them explicitly as control sites.

Table 14: Event Load Impacts (kW) for PY 2022-2025 Combined

	(1) Rate-to-Driver Workplace	(2) Rate-to-Driver MUD	(3) Rate-to-Host
Local Event Hour	-34.26*** (8.163)	-18.35** (8.939)	-36.73 (46.00)
System Event Hour	-10.66** (4.360)	-20.57** (9.935)	59.82 (43.15)
Local and System Event Hour	19.08*** (7.105)	11.85 (13.98)	10.79 (14.46)
Event Anticipation Hour	2.980 (2.527)	1.796 (2.914)	35.42 (21.80)
Event Rebound Hour	1.804 (2.506)	2.784 (2.382)	41.63 (27.31)
Observations	3,224,876	2,769,187	1,745,157
Sites	92	79	51
Avg. kWh	47.415	61.303	134.334
Avg. Local Event kWh	32.152	17.531	193.352
Avg. System Event kWh	21.490	53.332	98.782
Adj R-Squared	0.3146	0.5350	0.2925
Adj Within R-Squared	0.0006	0.0005	0.0002
	(1)	(2)	(3)

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The sample period covers October 1, 2021, through September 30 2025. Standard errors are two-way clustered at the site and hour-of-sample level. Estimated effects are at the site-level and include fixed effects for site, date, day-of-week, weekend-by-hour-of-day, and temperature bin. Rate-to-host results are reported for MUDs and workplace combined because there is a single MUD site.

Table 15 presents local- and system-event impacts in relative (%) terms for the average site for each type. The table includes coefficient estimates and standard errors from three separate Poisson regressions: rate-to-driver, workplace estimates shown in column (1); rate-to-driver, MUD estimates are presented in column (2); and rate-to-host estimates are presented in column (3). These estimates pool data from program years 2022 to 2025. On average, rate-to-driver workplace sites delivered load reductions of 60.5% during local event hours and 47.6% during system event hours. On average, rate-to-driver MUD sites delivered load reductions of 54.8% during local event hours and 33.4% during system events hours. These impacts are relatively large and are all statistically significant at the 1% level.

Table 15: Event Load Impacts (%) for PY 2022 -2025 Combined

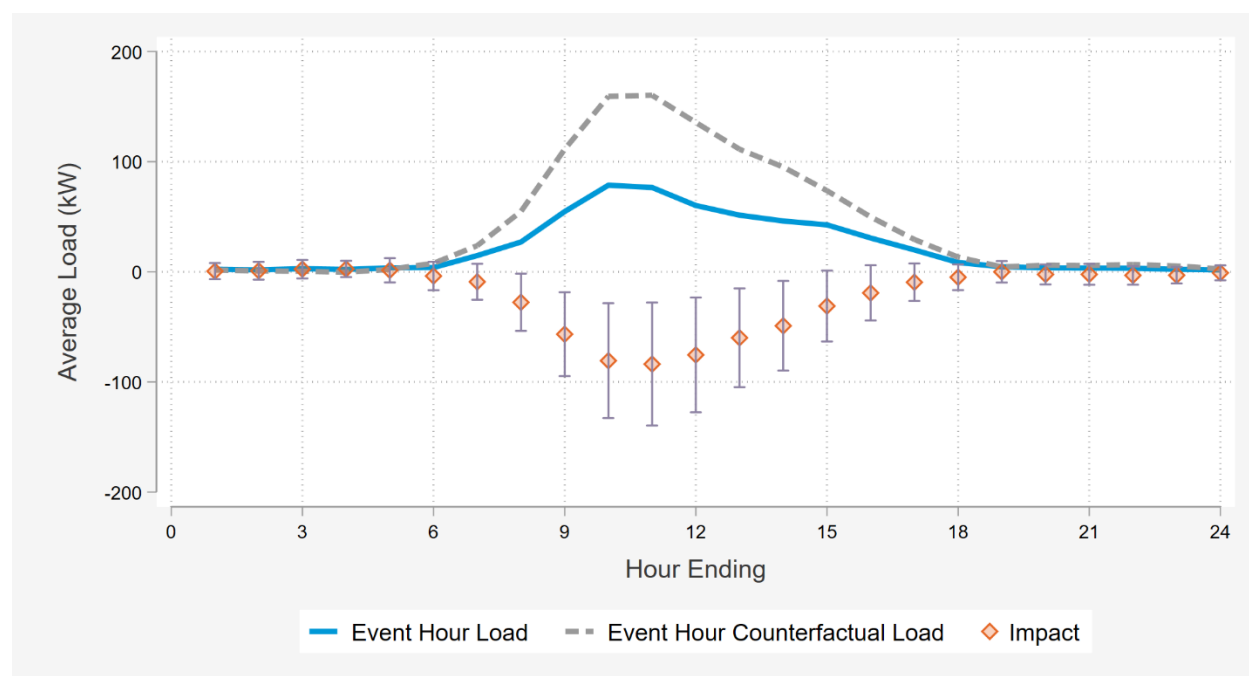
	(1)	(2)	(3)
	Rate-to-Driver	Rate-to-Driver	
	Workplace	MUD	Rate-to-Host
Local Event Hour	-0.605*** (0.126)	-0.548*** (0.0544)	0.277*** (0.0956)
System Event Hour	-0.476*** (0.0946)	-0.334*** (0.102)	0.301*** (0.0571)
Local and System Event Hour	0.184 (0.132)	-0.202 (0.190)	-0.245*** (0.0701)
Event Anticipation Hour	-0.0476 (0.0487)	0.0100 (0.0291)	0.167*** (0.0247)
Event Rebound Hour	-0.0177 (0.0440)	0.0174 (0.0203)	0.131*** (0.0322)
Observations	3,224,876	2,769,187	1,745,157
Sites	92	79	51
Pseudo-R-Squared	0.7535 (1)	0.7664 (2)	0.8689 (3)

Note: *** p<0.01, ** p<0.05, * p<0.1. This table reports coefficient estimates and standard errors from three separate Poisson regressions. The sample period covers October 1 2021 through September 30 2025. Standard errors are two-way clustered at the site and hour-of-sample level. Estimated effects are at the site-level and include fixed effects for site, date, day-of-week, weekend-by-hour-of-day, and temperature bin. Rate-to-host results in column (3) are reported for MUD and workplace combined because there is a single MUD site. Fixed effects in column (3) are interacted with MUD/workplace status.

Figure 31 and Figure 32 show estimates of average hourly site-level impacts at rate-to-driver workplace sites for local events and system events, respectively. These coefficient estimates, confidence intervals, and load shapes, are from Equation 2 estimated on rate-to-driver workplace sites, with the addition of hourly dummy variables interacted with local event and system event variables. Event hour load and event hour counterfactual load are from model predictions. Note that because events were called at different times on each event day, each hourly impact is estimated using a different set of days, and each hourly impact is estimated using a different number of events. The average event hour estimates presented in Table 14 above represent a weighted average of these hourly estimates where the weights correspond to the number of events called that included each hour. These hourly estimates are best

interpreted as average impacts for the average event that included that hour.¹¹ For local event impacts shown in Figure 31, every hour is represented; for every hour, there exists at least one event in the sample that included that hour. In Figure 32, there are no impact estimates in early morning hours because no system events were called in those hours. Examining these graphs, we see that the large demand reductions occur in hours where load is highest. When load impacts are statistically significant, they are large relative to the counterfactual load for that hour. Local events, which are more likely to occur in the middle of the day when workplace load is highest, have larger, more precisely estimated load impacts than local events.

Figure 31: Local Event Estimated Average Hourly Site-Level Impacts for Workplace Rate-to-Driver Sites



¹¹ Often, in demand response load impact evaluations, graphical and/or hourly estimates are presented for the average event day, and for individual event days. In this instance, because events were called at many different times, average event day impacts by hour will attenuate hourly impacts, because they represent an average for that hour over many days, only some of which were event days. Individual event day impacts are not shown because of the large number of event days called for a subset of the population; not only is showing so many individual days infeasible, individual day impacts would be subject to too much uncertainty to be statistically meaningful.

Figure 32: System Event Estimated Average Hourly Site-Level Impacts for Workplace Rate-to-Driver Sites

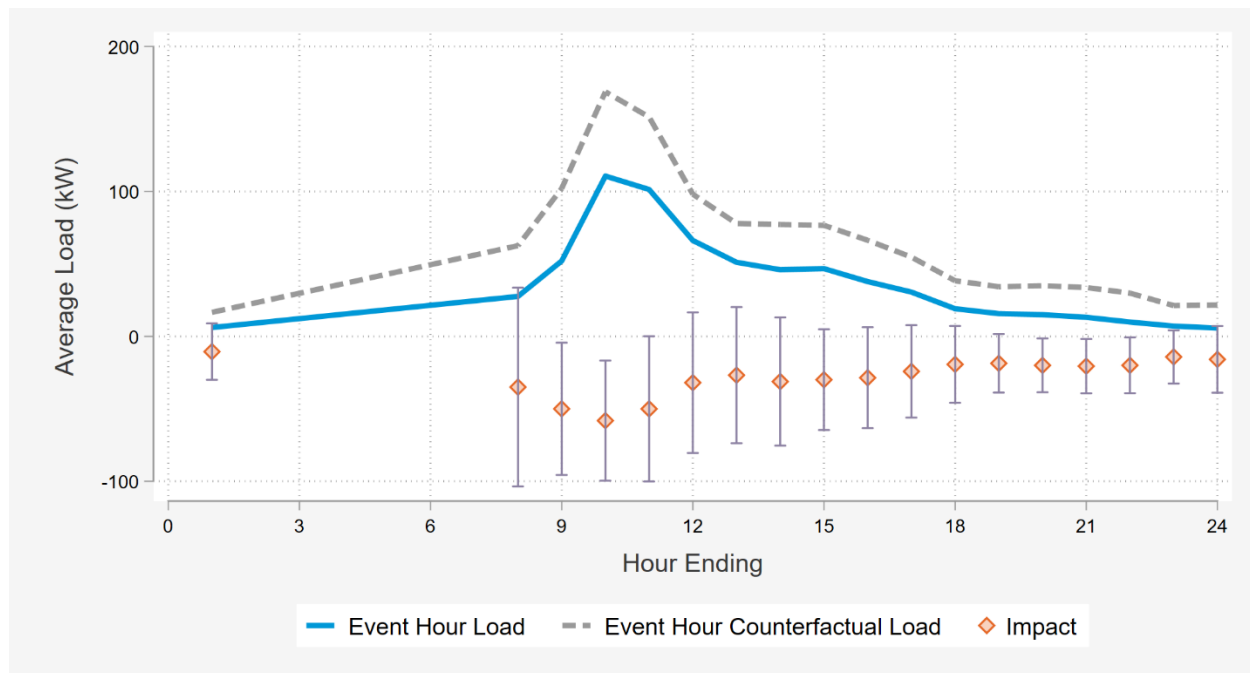


Figure 33 and Figure 34 show estimates of average hourly site-level impacts at rate-to-driver MUD sites for local events and system events, respectively. As was the case for workplace site estimates presented above, these coefficient estimates, confidence intervals, and load shapes are from Equation 2 estimated on rate-to-driver workplace sites, with the addition of hourly dummy variables interacted with local event and system event variables. Examining these graphs, we see that the large demand reductions occur in hours where load is highest. When load impacts are statistically significant, they are large relative to the counterfactual load for that hour. Relative to workplace estimates presented above, MUD counterfactual load is higher in the evening when drivers are more likely to be at home and charging their vehicles.

Figure 33: Local Event Estimated Average Hourly Site-Level Impacts for MUD Rate-to-Driver Sites

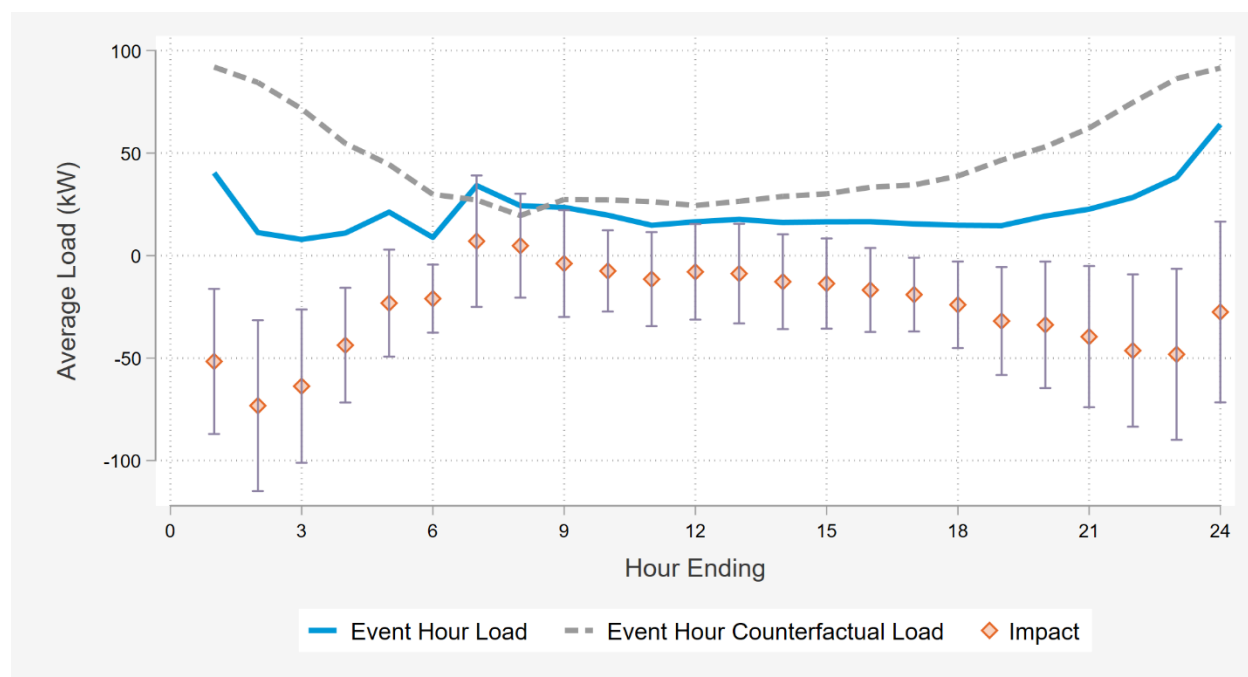
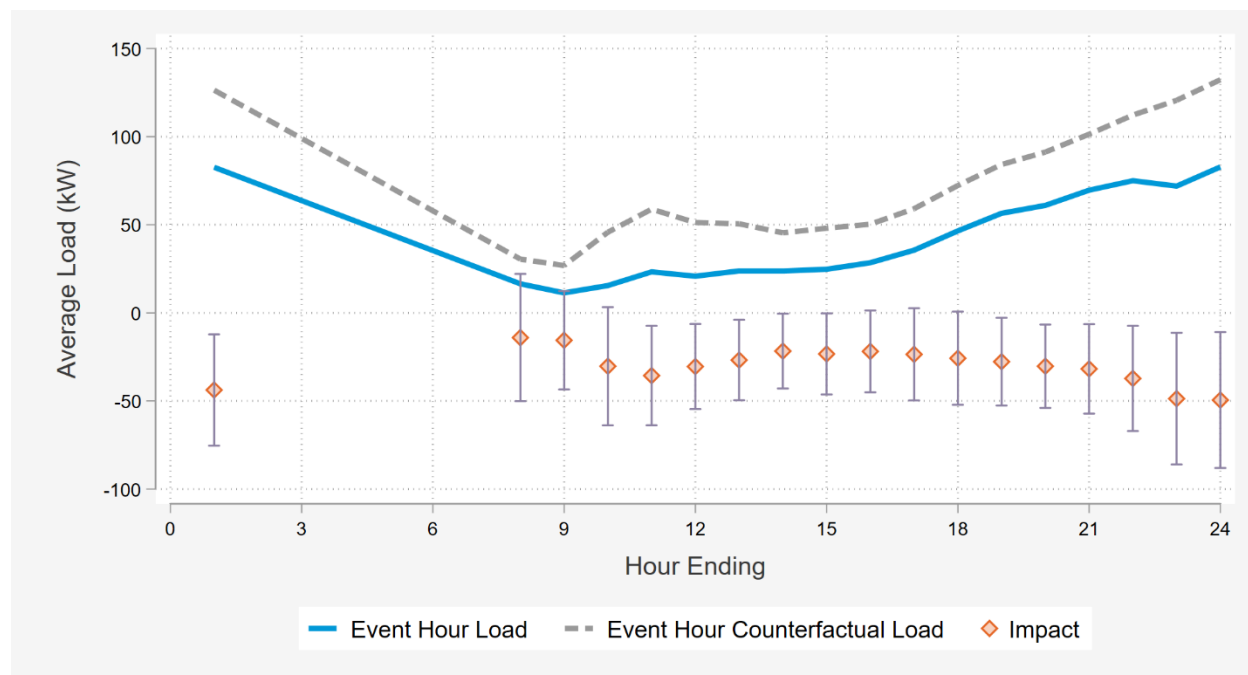


Figure 34: System Event Estimated Average Hourly Site-Level Impacts for MUD Rate-to-Driver Sites



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