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2024 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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ACKNOWLEDGEMENTS

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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 0.35 at workplaces, and 0.25 at MUDs. We find little evidence of price sensitivity at sites where drivers do not pay for charging.

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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 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 1: 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	-26.41***	-11.49***	-0.624***	-0.472***
Rate-to-Driver MUD	80	-17.68**	-14.01*	-0.524***	-0.294***
Rate-to-Host	51	-36.83	30.72	0.0679	0.154***

Note: *** p<0.01, ** p<0.05, * p<0.1. Negative coefficients represent load reductions. Over the 3-year analysis period, local events were called on 164 days, and system events were called on 44 days.

Table 2 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 2.5% and 3.5% 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 2: Price Elasticity Estimates Summary

Sector	Sites	Obs.	Price Elasticity	Std. Err
Rate-to-Driver Workplace	92	2,416,935	-0.346***	-0.0607
Rate-to-Driver MUD	80	2,102,747	-0.248***	-0.0357
Rate-to-Host	51	1,317,335	0.0612**	-0.0257

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

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 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.

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

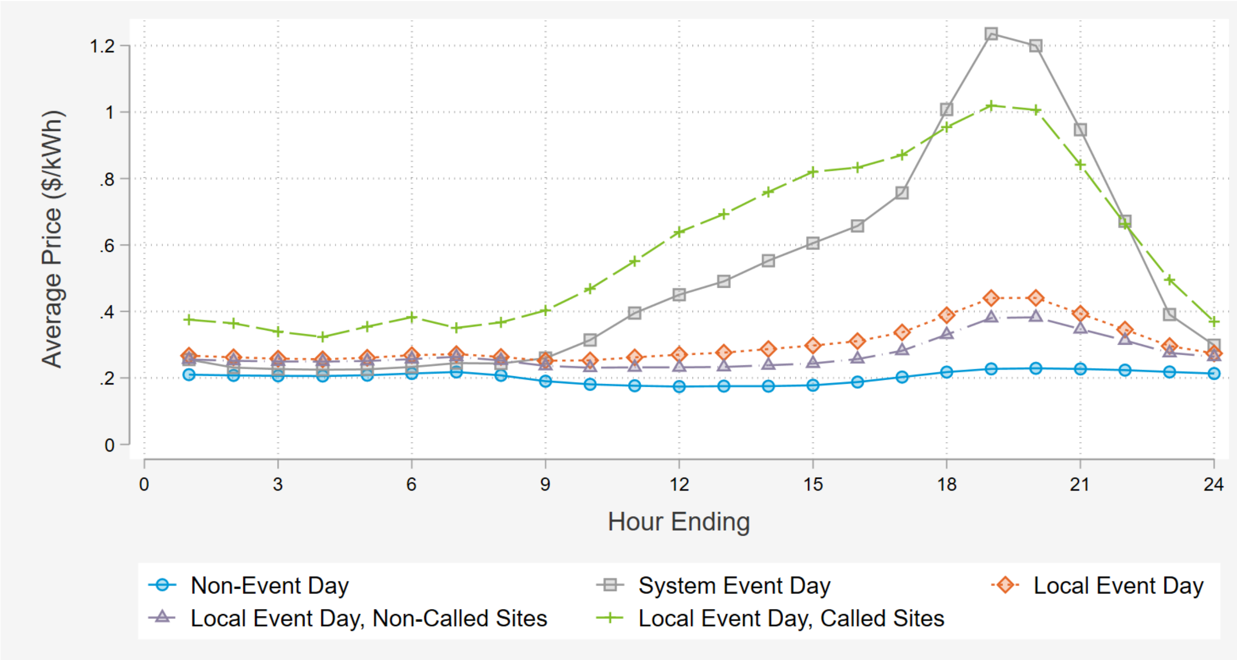
- ✓ A system adder that targets the top 150 system load hours (based on CAISO demand) to reflect the costs of generation capacity, which is needed to meet peak demand levels.
- ✓ A distribution rate adder or circuit adder targets the top 200 load hours of the distribution circuits that the charger is 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 2021 through PY 2023 (10/1/2021—9/30/2024). 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 2021-PY 2023



The remainder of this section provides context and additional detail about the VGI rate. It details the key research questions, summarizes 2022-2024 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:

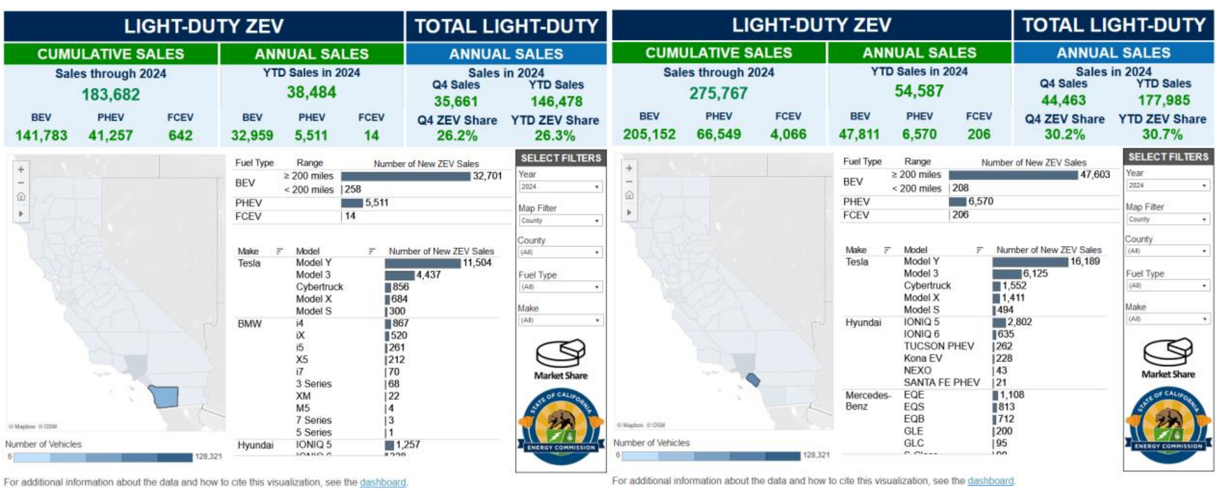
- How many charging stations are enrolled by customer type, and how has this changed over time?
- What is the utilization of charging stations by customer segment (rate-to-driver, rate-to-host, MUD, workplace, DAC, non-DAC, workplace type)?
- How much price variation is there in local events across circuits? How correlated are local and system events?
- What were the demand reductions due to the Vehicle Grid Integration events? Did demand reductions differ for system events and local events?
- How do load impacts differ for different types of customers (rate-to-driver, rate-to-host, MUD, workplace)?
- How price-responsive are customers to the VGI rate? Does that price responsiveness vary by site type?
- 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 fundamentally transform the electric grid. 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 2.9M vehicles were registered with the California DMV in SDG&E's service territory[2], which includes all of San Diego County and portions of South Orange County. Over 130,000 electric vehicles and 40,000 plug-in hybrid electric vehicles (PHEV) were registered in SDG&E territory. While the share of electric vehicles is small (5.8%) relative to all vehicles in the service territory, the market share of electric vehicles has been growing exponentially, as shown in Figure 2. That said, this trend may have stabilized slightly in 2024. Specifically, electrified vehicles have grown as a share of new vehicles (100% battery electric or plug-in hybrid electric) through 2023. Focusing on San Diego County, in 2024 26% of new vehicles sold were either full electric vehicles or plug-in hybrid vehicles in 2024, which is the same share as in 2023. The historical market share penetration data has matured enough that the new vehicle share adoption can be estimated using historical data, as shown in Figure 3.

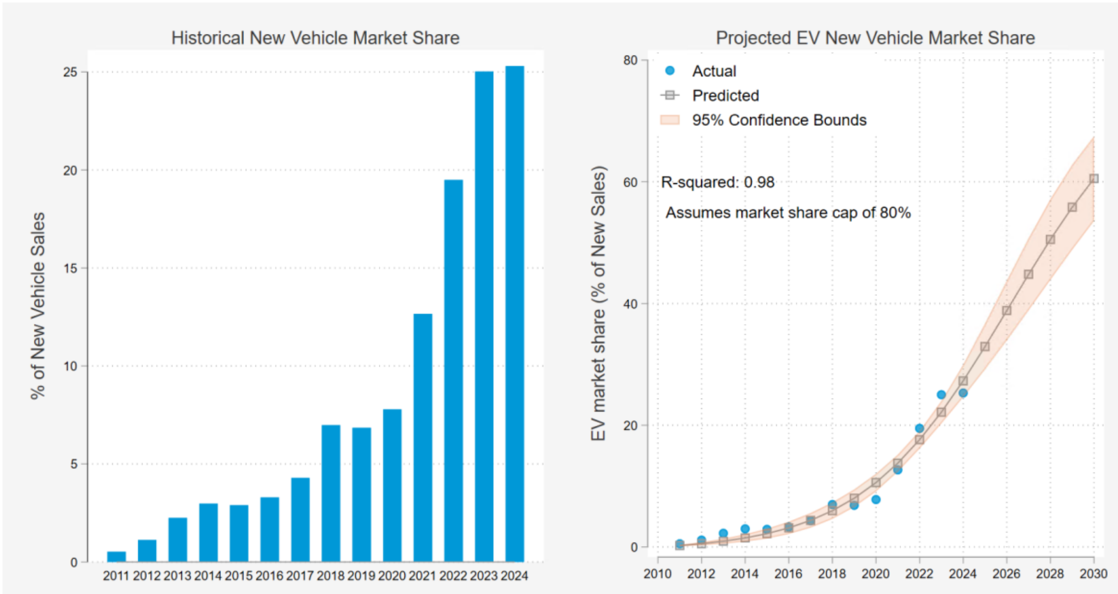
Figure 2: Electric Vehicle Population in SDG&E Territory (2024)



Source: California Energy Commission (2025). New ZEV Sales in California. Data last updated December 31, 2024. Retrieved February 18, 2025, from https://www.energy.ca.gov/zevstats

[2] Source: California Energy Commission (2025). Data last updated December 31,2024. Retrieved February 18, 2025.

Figure 3: Electric Vehicle Market Share of New Vehicle Sales



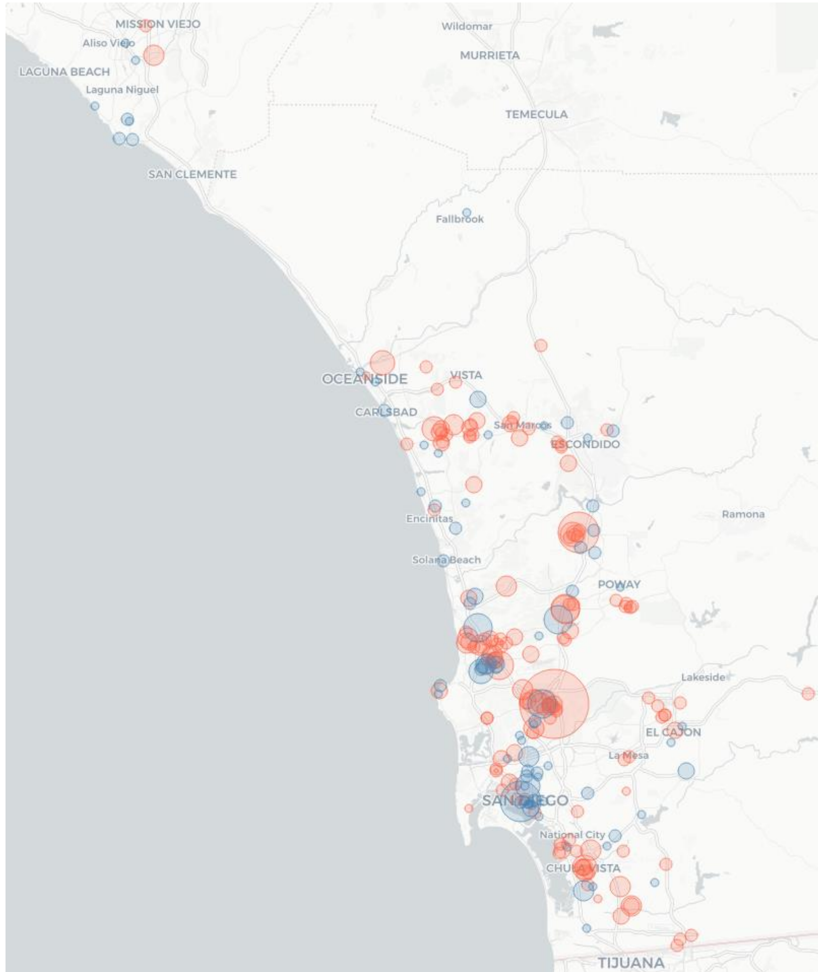
Data source: California Energy Commission (2024). New ZEV Sales in California. Retrieved February 18, 2025, from https://www.energy.ca.gov/zevstats Graphs and market share projection produced by DSA.

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 223 sites in total.
- 169 sites are registered for rate-to-driver billing, representing 76% of the total 223 sites analyzed.
- 81 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 2024 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 5,000 MW[3]. 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.

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[3] SDG&E system demand peaked at 5,032 MW on Sunday September 8th 2024 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. Time-varying prices, such as PYD's 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. In 2024, peak demand at both SDG&E and CAISO was high compared to historical years: SDG&E peaked at 5,032 MW, CAISO peaked at 47,759 MW, and CAISO net loads peaked at 43,276 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 the demand in the top 1% of hours at SDG&E was reduced, that could provide up to a 26% reduction (1,263 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 18% reduction (~7,950 MW) in need for generation capacity. Figure 7 shows the hourly electricity market prices for the SDG&E area from May to September 2024. The high price periods coincided with times when CAISO net loads were highest. Demand Response / dynamic pricing programs therefore offer large price savings by avoiding costs during the most constrained system hours.

Figure 5: SDG&E and CAISO Top Ten Peak Load Days (Oct 2023-Sep 2024)

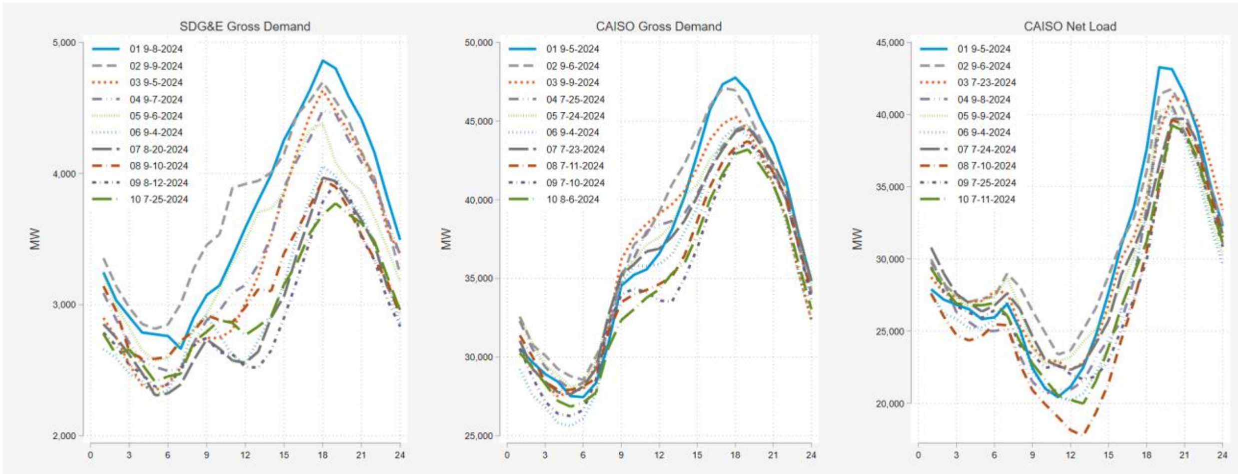


Figure 6: Normalized Load Duration Curves for Top 5% of Hours (Oct 2023-Sep 2024)

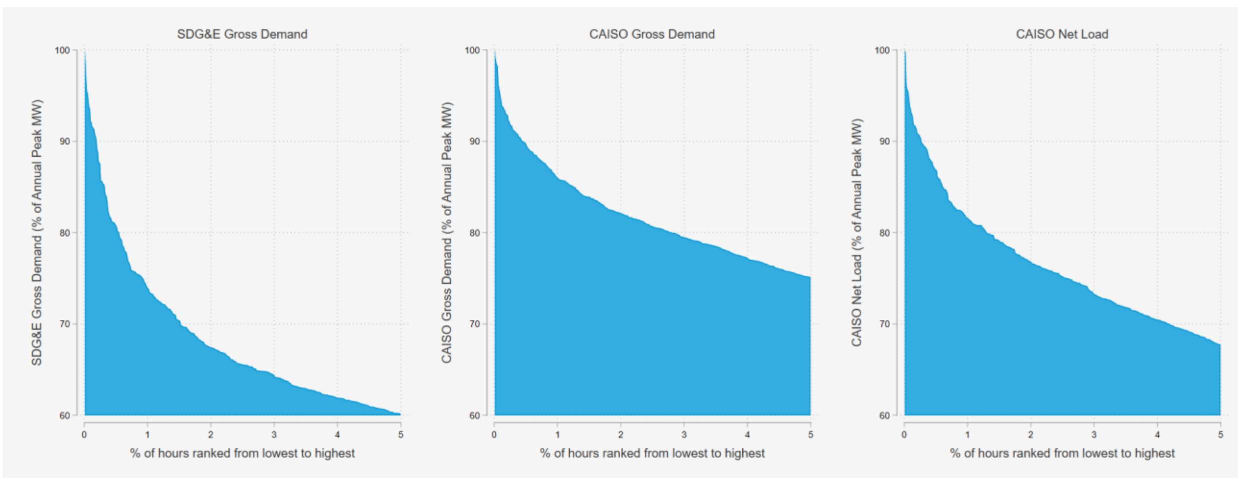
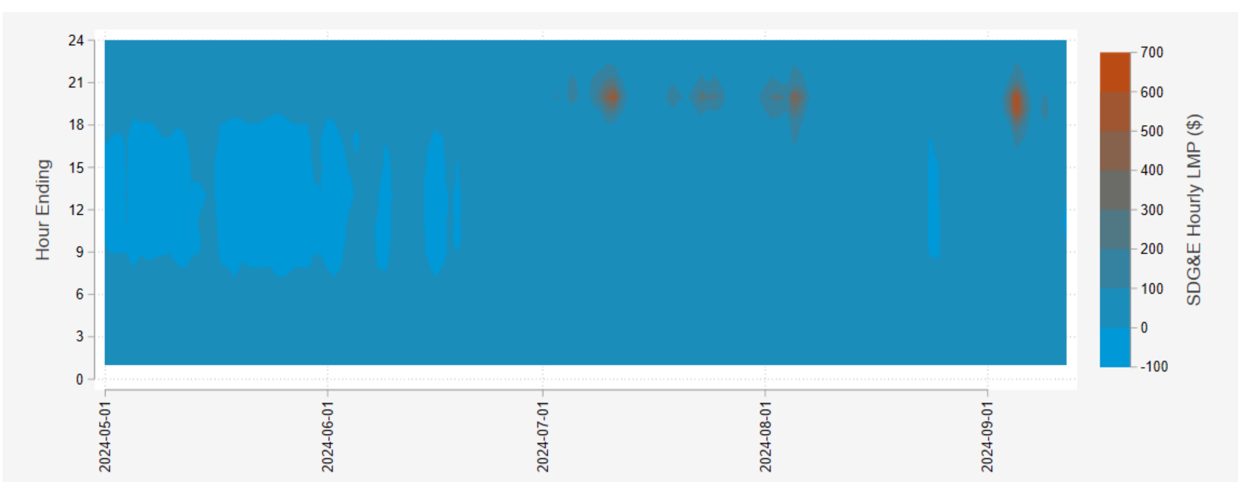


Figure 7: SDG&E Summer 2024 Hourly Electricity Market Prices



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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 223 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 2024 (October 1 2021 through September 30 2024). The data are at the site-hour-level. Average demand is 33 kWh for rate-to-driver workplace sites and 44.6 kWh for rate-to-driver MUD sites, and 89.6 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 40 and 50 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 $0.27, but price has a relatively large standard deviation of about $0.20 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	32.91	132.22	0	3900
	kWh > 0	0.82	0.39	0	1
	System Event	0.02	0.15	0	1
	Local Event	0.02	0.13	0	1
	Price ($/kWh)	0.27	0.20	0	3.44
	Hourly Temp. (F)	62.20	9.59	22.82	111.74
RTD, MUD	kWh	44.63	158.50	0	5354.40
	kWh > 0	0.90	0.30	0	1
	System Event	0.02	0.15	0	1
	Local Event	0.01	0.11	0	1
	Price ($/kWh)	0.26	0.20	0	2.98
	Hourly Temp. (F)	62.44	9.83	22.82	111.74
RTH	kWh	89.64	582.46	0	14960
	kWh > 0	0.83	0.37	0	1
	System Event	0.02	0.15	0	1
	Local Event	0.01	0.12	0	1
	Price ($/kWh)	0.27	0.19	0	3.44
	Hourly Temp. (F)	61.87	10.44	22.82	111.74

Note: Rate-to-driver, workplace has 808,036 observations. Rate-to-driver, MUD has 701,680 observations. Rate-to-host has 441,670 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 $0.83 is in place, and during local events, an hourly adder of $0.84 is in place. Figure 8 shows a heat map of the proportion of sites subject to system events by hour and date. When a system event is in place, all sites are subject to the event. 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

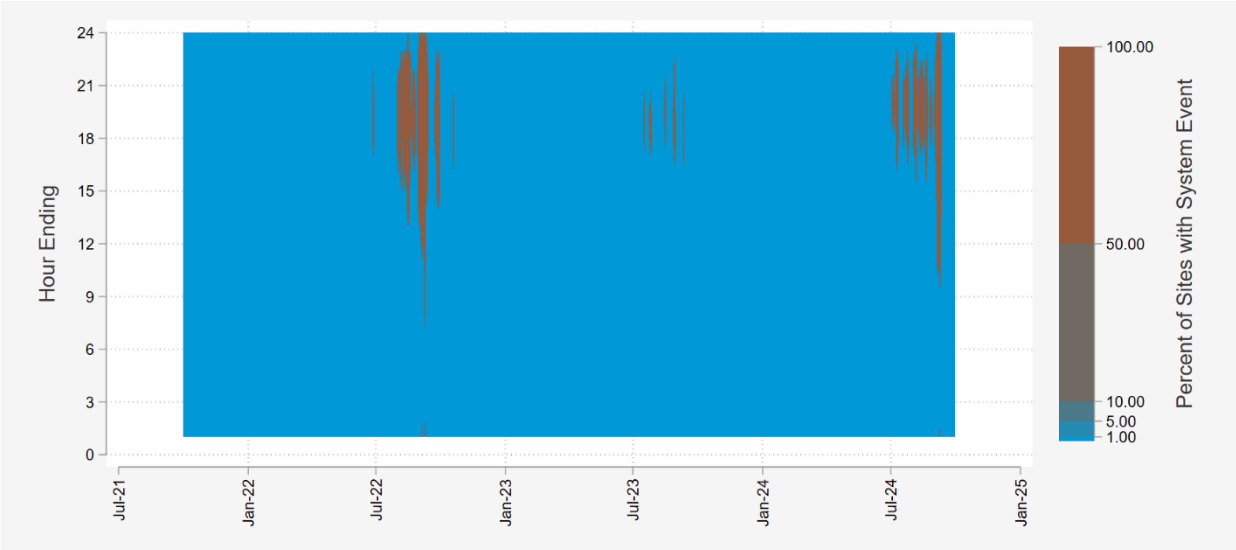


Figure 9 shows a heat map of the proportion of site subject to local events by hour and date. First, in contrast to system events, which are either in place for all sites or none, the share of sites subject to local events is often somewhere between 0 and 100. Before summer 2022, a small share of sites 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 9: Share of Site Subject to Local Events by Date and Hour

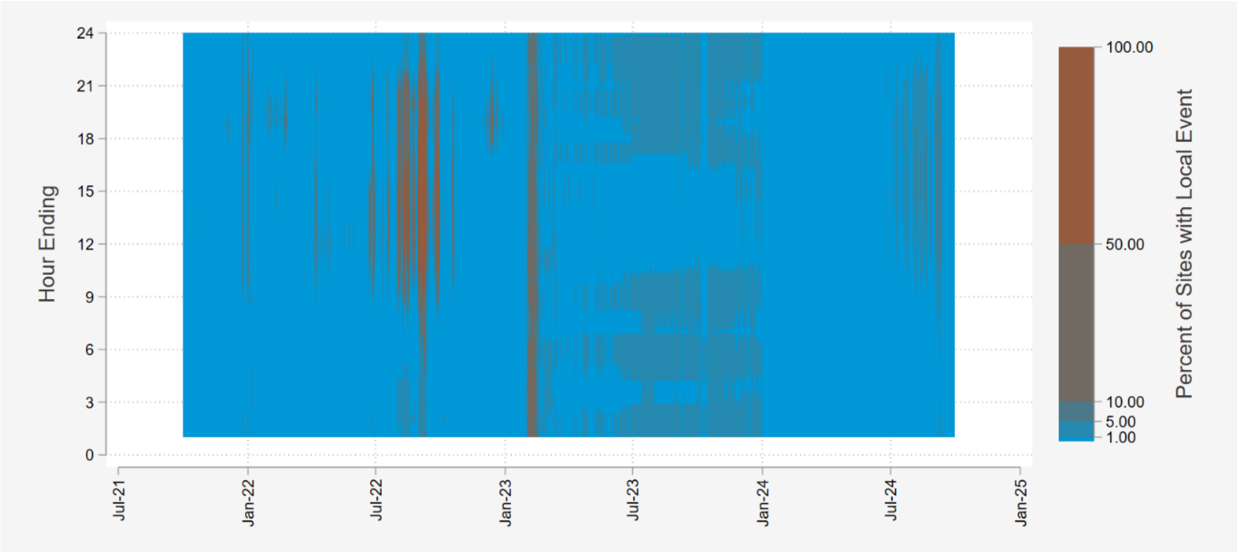


Figure 10 shows a heat map of the hourly price for the average site by date and hour. The hourly price is the base rate plus the day ahead hourly wholesale price plus any adders in effect. The highest average prices, over $2.50/kWh occur when both system and local events are in place. Otherwise, there are many days throughout 2024 when the price at the average site is above $0.50.

Figure 10: Vehicle Grid Integration Prices by Date and Hour

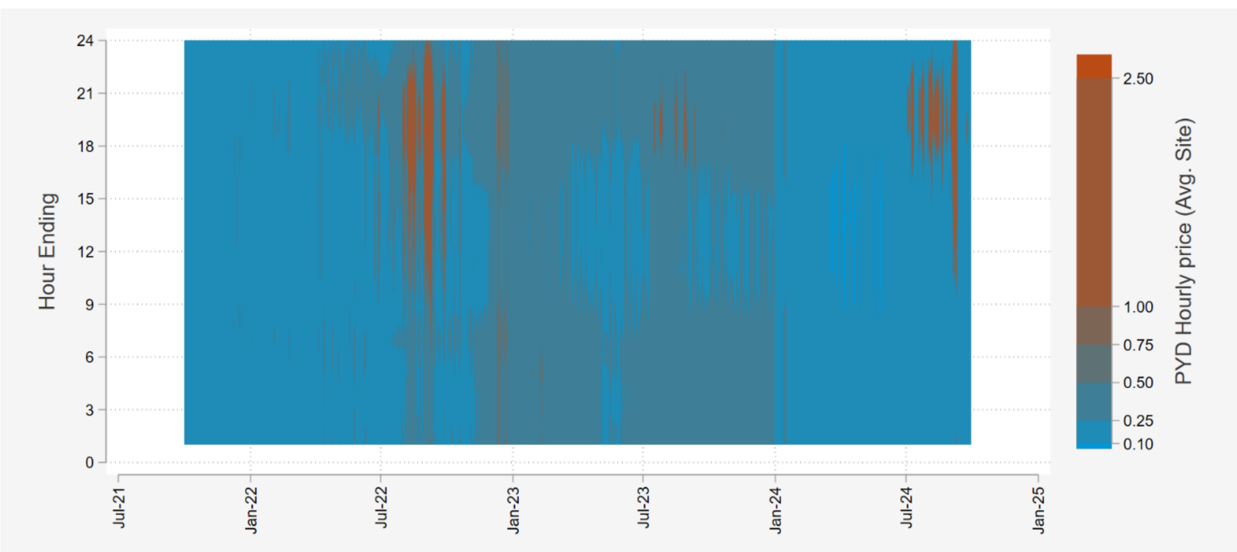
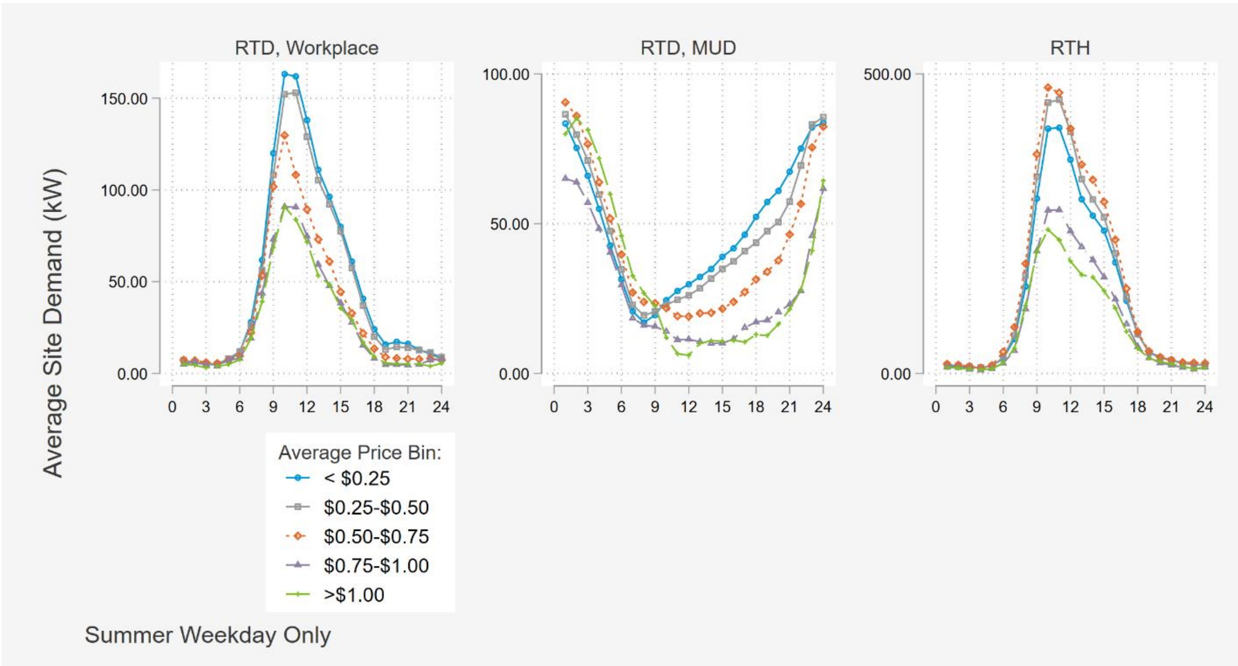


Figure 11 shows average hourly consumption patterns by average daily price discretized into bins for 2022-2024 summer weekdays by the site type. The relationship between price and charging patterns is very clear for rate-to-driver sites. In general, when prices are high, vehicle charging decreases. For 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



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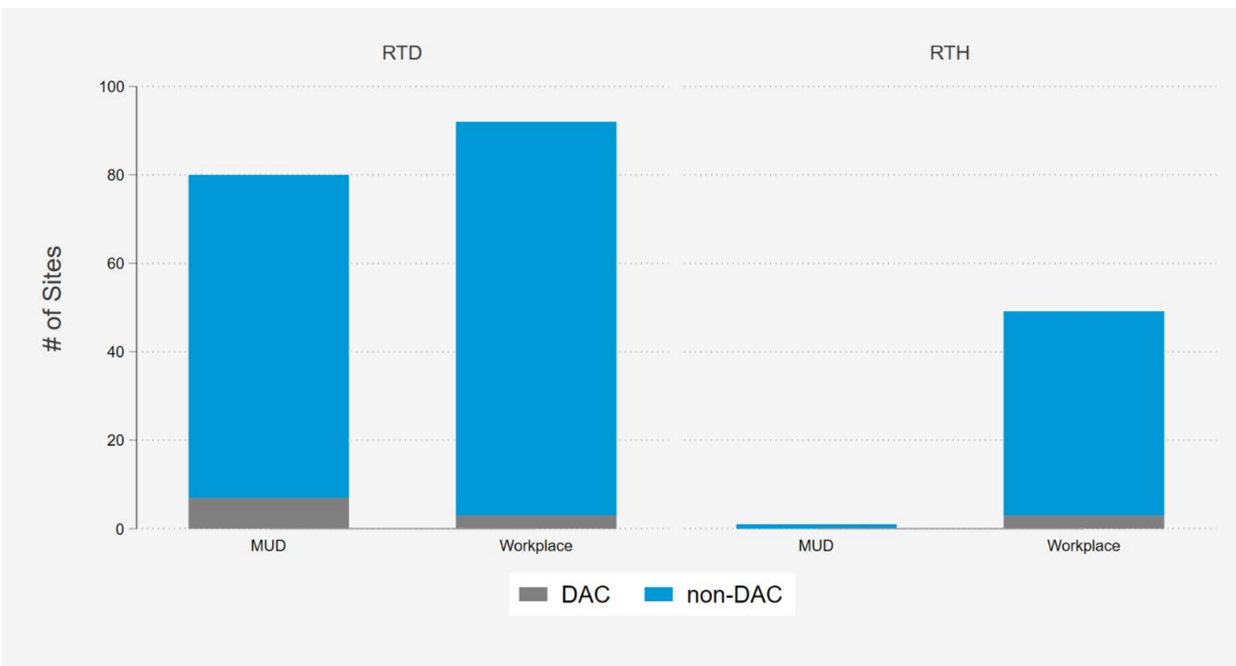
4 PROGRAM DEPLOYMENT AND UTILIZATION RESULTS

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 2024. (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, 2024), 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

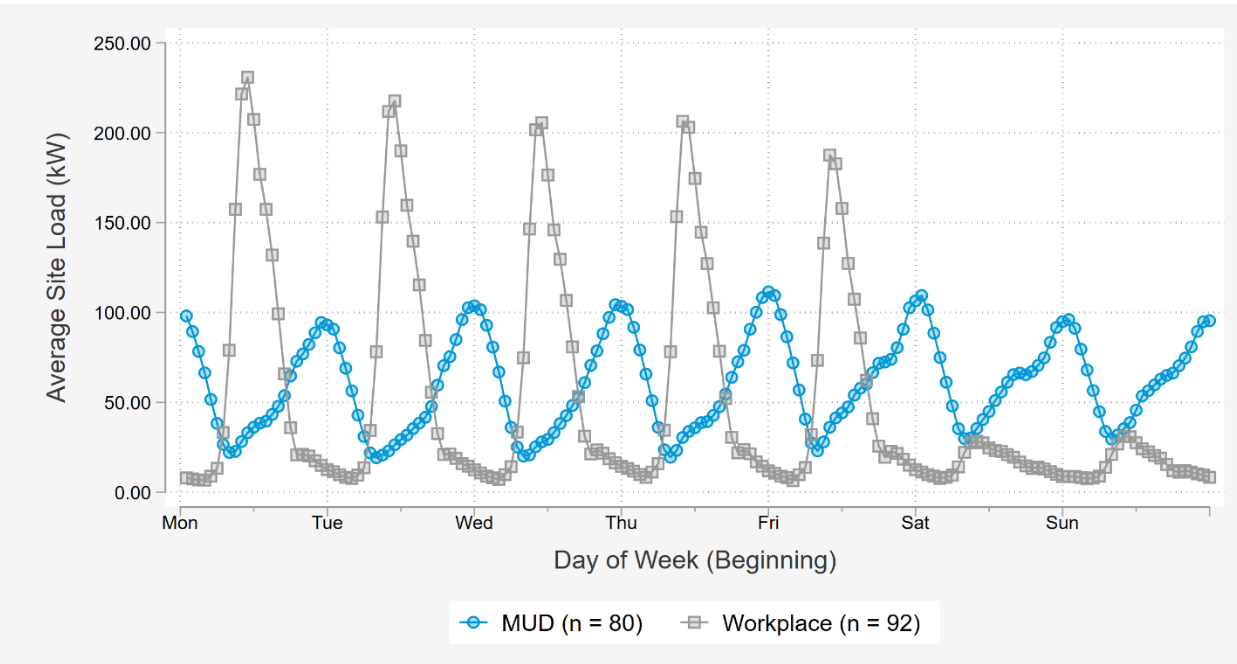
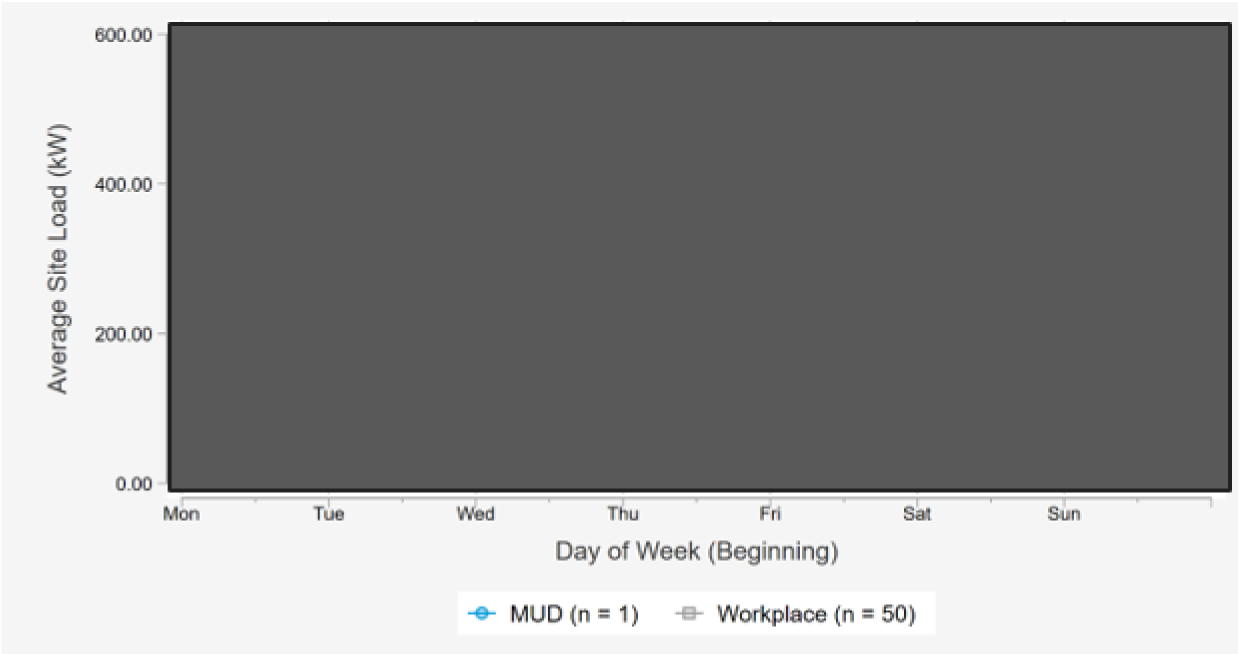


Figure 14 plots the weekly average load shape rate-to-host sites. The graph shows the observed load for program year 2024 (October 1 2022 through September 30 2024), and includes all hours, including event hours. There is a single MUD site whose charging load appears similar to that of workplace sites, 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 Sites[4]



In Figure 16, 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.

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[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 Sites[5]

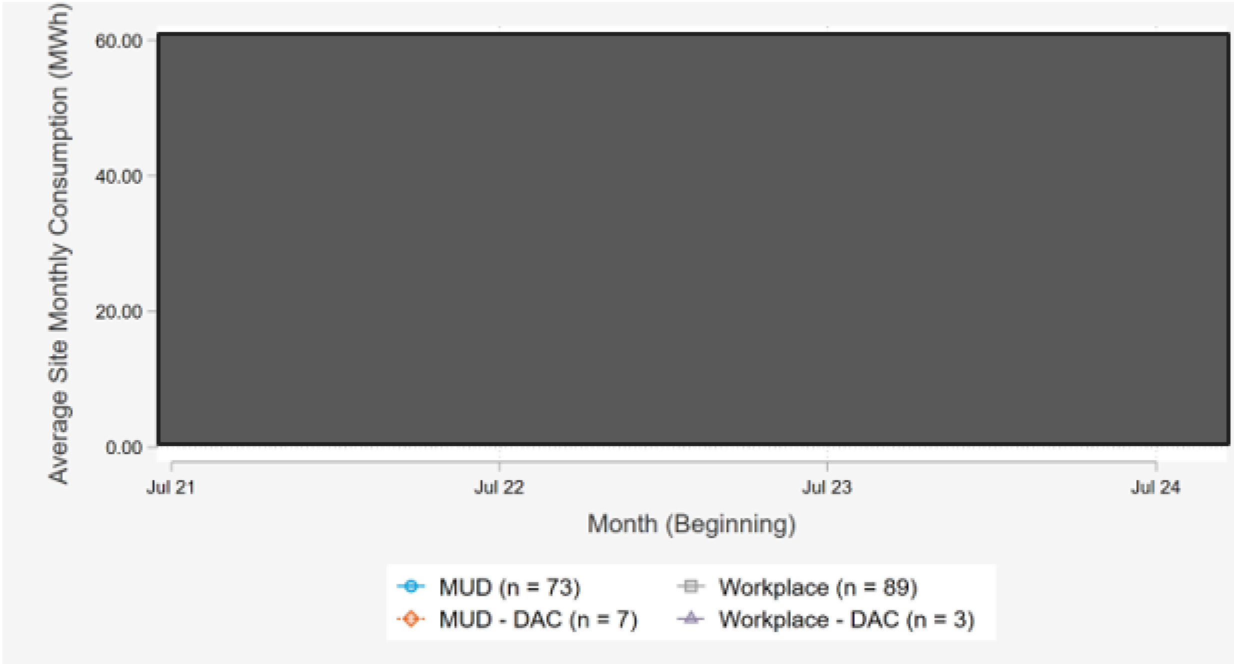
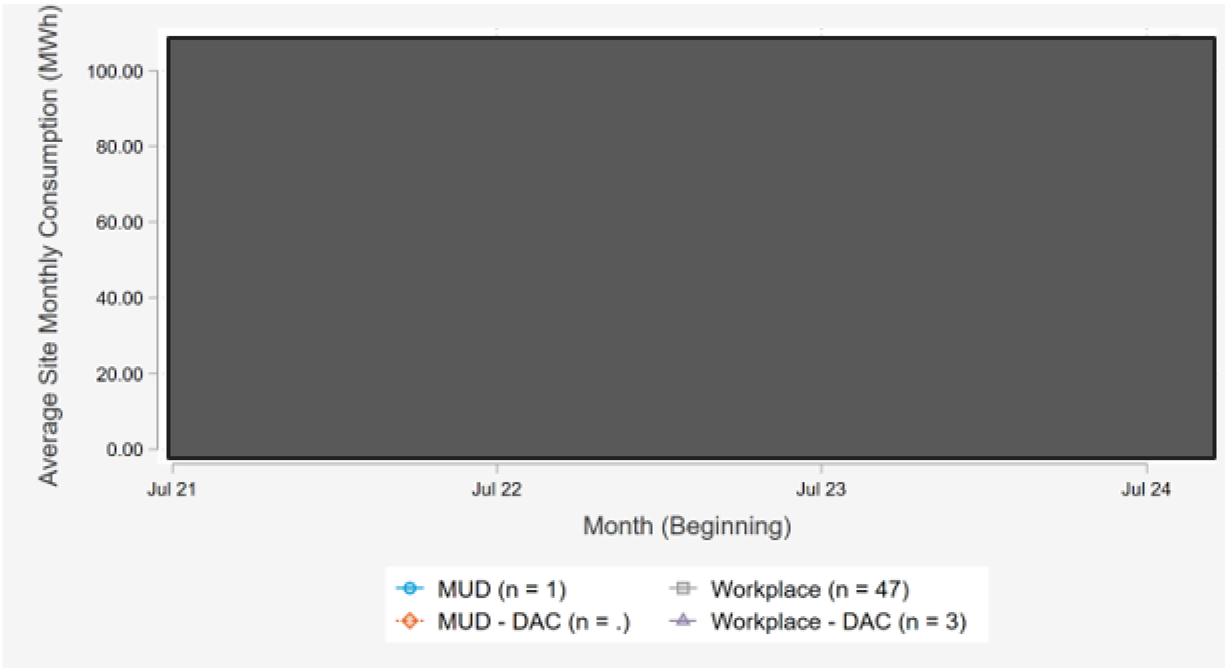


Figure 16 shows the monthly consumption for average rate-to-host sites for each type of site. Workplace consumption at rate-to-host sites is much higher than at rate-to-driver sites. Some rate-to-host sites are very large. It is also possible that at rate-to-host sites, drivers substitute all their charging 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 Sites[6]



[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 multi-family chargers are enrolled in the SDG&E program, making it challenging to develop a control group that did not face the dynamic rates. Our empirical strategy relies 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.
- 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 present 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.

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, 2024 were provided for the evaluation. We analyzed charging throughout this period.
2.	**Data included in the analysis**	For the VGI evaluation, we utilized: ▪ 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**	Panel regression by charging site with multiple fixed effects. We implemented an event response model, which treated periods with generation or distribution capacity adders as events, and a price response model. The price response model estimated price elasticities (% change in load associated with a 1% change in prices). The event-based model flagged hours with local or system Critical Peak Pricing adders as events. The coefficients of these models demonstrate the magnitude of customer response to pricing changes and event hours.
4.	**Model selection**	To estimate customer response, we used OLS and Poisson regression models fixed effects. We provide a detailed discussion below.
5.	**Segmentation of impact results**	The results will be segmented by: ▪ Site type: Workplace vs. Multi-Unit Dwellings ▪ Rate to Host vs. Rate to Driver

5.1 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 1 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 1: Event Response OLS Model Specification

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

Table 5 defines each model term in the equations above.

Table 5: 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.[7] We finally include hour-by-weekend/weekday fixed effects to control for hourly variation in load that differs by weekend/weekday.

[7] 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.

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 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 Poission random variable with parameter $\lambda_{it} > 0$. We model λ_{it} as an expontential function of the covariates in the linear model above (excluding the error term):

Equation 2: Event Response Model Poisson Specification

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

where,

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

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.

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 5 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 3: Price Elasticity Model Poisson Specification

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

where,

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

The coefficient of interest is γ_1, the elasticity of load with respect to price. The elasticity in percentage terms is given by γ_1x 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.

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, 2024.

6.1 LOAD IMPACTS OF SYSTEM AND DISTRIBUTION ADDERS

Table 6 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 26.41 kW during local event hours and 11.49 kW during system event hours. On average, sites at rate-to-driver MUD sites delivered load reductions of 17.68 kW during local event hours and 14.01 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. The average local event hour is hour ending 14 and the average system event hour is hour ending 19. If we look at average load in those same average hours when events are not called, it is 113 kW in hour ending 14 and only 41 kW in hour ending 19. 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 price[8], we would be concerned our estimates for rate-to-driver sites were biased.

[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 6: Event Load Impacts (kW) for PY 2022-2024 Combined

	(1)	(2)	(3)
	Rate-to-Driver	Rate-to-Driver	
	Workplace	MUD	Rate-to-Host
Local Event Hour	-26.41***	-17.68**	-36.83
	(6.692)	(6.698)	(40.04)
System Event Hour	-11.49***	-14.01*	30.72
	(3.776)	(7.430)	(25.10)
Local and System Event Hour	16.59***	8.901	23.16
	(5.945)	(10.04)	(18.58)
Event Anticipation Hour	2.129	1.877	19.93
	(1.659)	(1.788)	(12.48)
Event Rebound Hour	0.175	0.736	26.64
	(1.568)	(1.364)	(18.05)
Observations	2,419,692	2,103,096	1,317,570
Sites	92	80	51
Avg. kWh	32.906	44.635	89.639
Avg. Local Event kWh	27.499	14.983	140.858
Avg. System Event kWh	16.823	41.869	69.967
Adj R-Squared	0.3085	0.5284	0.2795
Adj Within R-Squared	0.0009	0.0006	0.0003
	(1)	(2)	(3)

Note: *** p<0.01, ** p<0.05, * p<0.1. The sample period covers October 1, 2021, through September 30 2024. 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 7 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 2024. Program year 2024 estimates are shown in the Appendix. On average, rate-to-driver workplace sites delivered load reductions of 62.4% during local event hours and 47.2% during system event hours. On average, rate-to-driver MUD sites delivered load reductions of 52.4% during local event hours and 29.4% during system events hours. These impacts are large in relative terms and are all statistically significant at the 1% level.

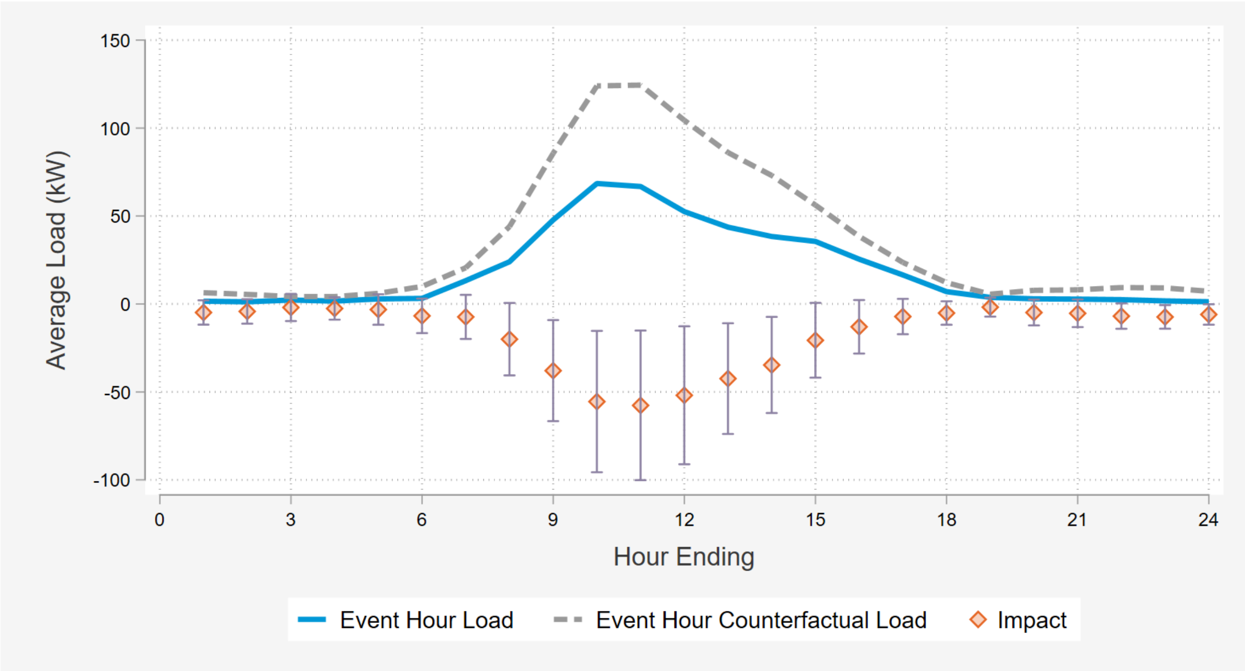
Table 7: Event Load Impacts (%) for PY 2022 -2024 Combined

	(1)	(2)	(3)
	Rate-to-Driver	Rate-to-Driver	
	Workplace	MUD	Rate-to-Host
Local Event Hour	-0.624***	-0.524***	0.0679
	(0.136)	(0.0544)	(0.0566)
System Event Hour	-0.472***	-0.294***	0.154***
	(0.101)	(0.101)	(0.0393)
Local and System Event Hour	0.219*	-0.183	-0.0920
	(0.120)	(0.165)	(0.0610)
Event Anticipation Hour	-0.0467	0.0383	0.0689***
	(0.0433)	(0.0248)	(0.0152)
Event Rebound Hour	-0.0208	-0.00377	0.0688***
	(0.0411)	(0.0216)	(0.0245)
Observations	2,419,692	2,103,096	1,317,570
Sites	92	80	51
Pseudo-R-Squared	0.7407	0.7536	0.8668
	(1)	(2)	(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 2024. 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 17 and Figure 18 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 1 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 6 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.[9] For local event impacts shown in Figure 17, every hour is represented; for every hour, there exists at least one event in the sample that included that hour. In Figure 18, 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 17: Local Event Estimated Average Hourly Site-Level Impacts for Workplace Rate-to-Driver Sites



[9] 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 18: System Event Estimated Average Hourly Site-Level Impacts for Workplace Rate-to-Driver Sites

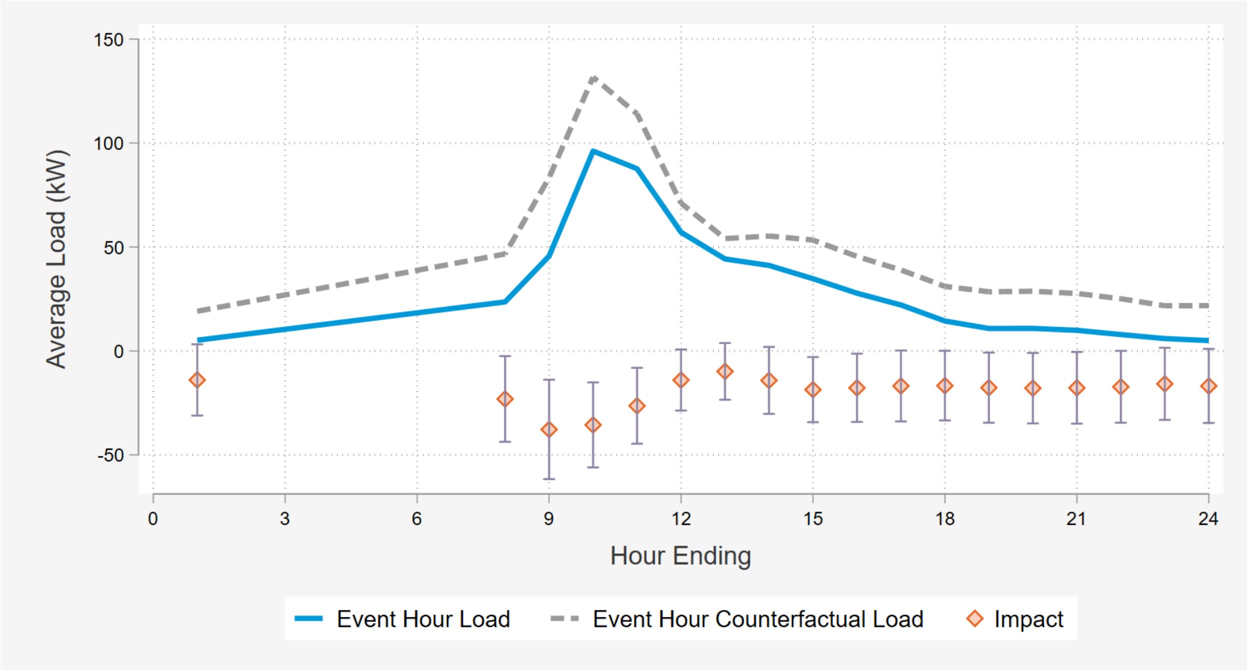


Figure 19 and Figure 20 show estimates of average hourly site-level impacts at rate-to-driver MUD sites for local events and system events, respectively. As was the case for workplace site estimates presented above, these coefficient estimates, confidence intervals, and load shapes are from Equation 1 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.

We present hourly impacts for rate-to-host sites, which did not yield statistically significant load impacts for the average event hour, in the Appendix.

Figure 19: Local Event Estimated Average Hourly Site-Level Impacts for MUD Rate-to-Driver Sites

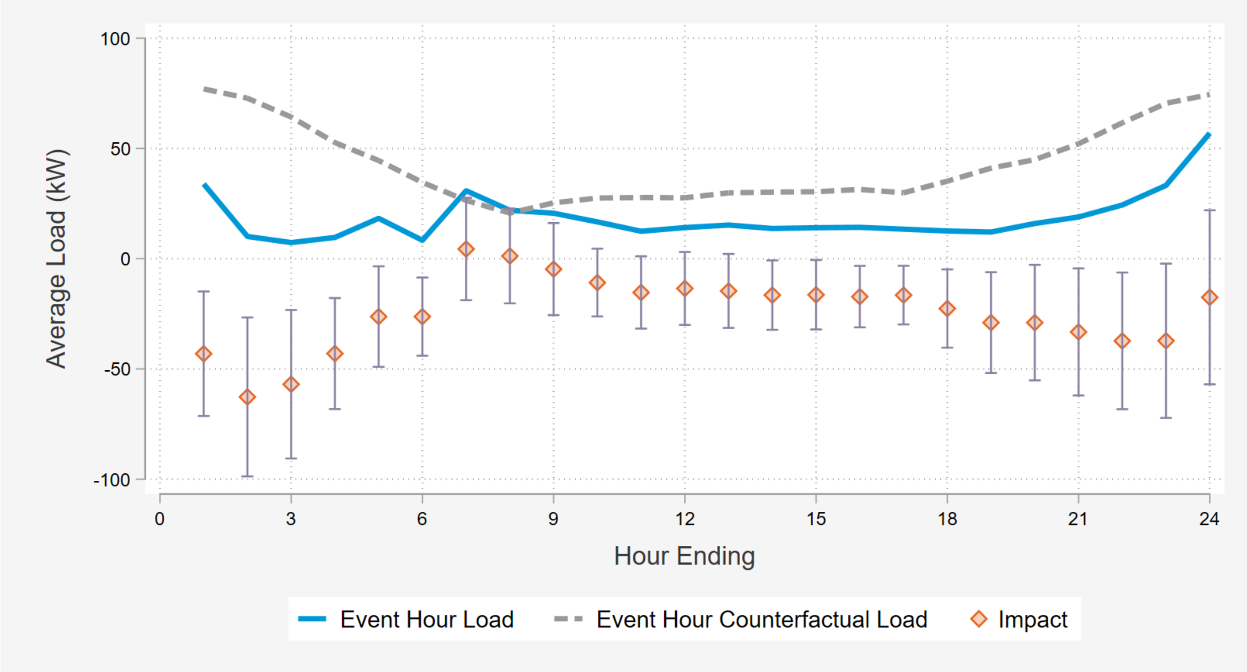
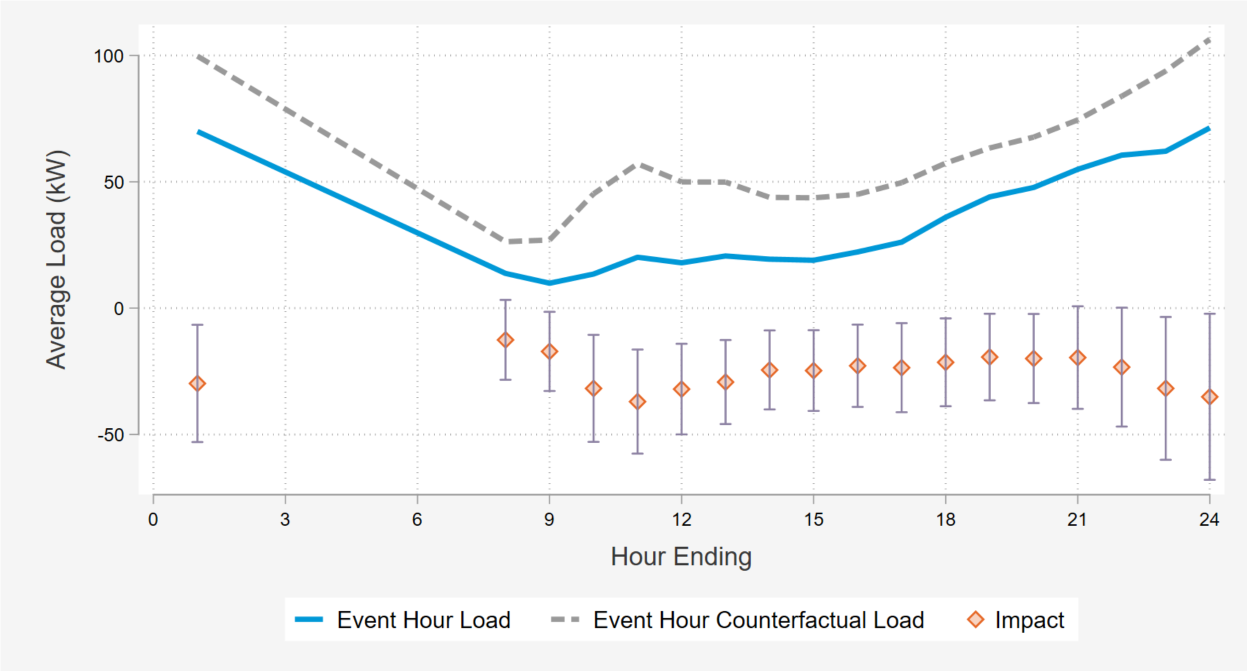


Figure 20: System Event Estimated Average Hourly Site-Level Impacts for MUD Rate-to-Driver Sites



6.2 PRICE SENSITIVITY

Table 8 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 2024. The estimate of -0.346 at rate-to-driver workplace sites indicates that, on average, drivers decrease their charging by 3.5% for each 10% increase in prices. At MUD sites, the price responsiveness is slightly less. Drivers decreased their charging by 2.5% 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 result 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 at 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 positive[10] 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 statistically significant negative price elasticities at rate-to-host sites, where there is no reason to expect drivers to respond to price[11], we would be concerned our estimates for rate-to-driver sites were

[10] 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.

[11] 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.

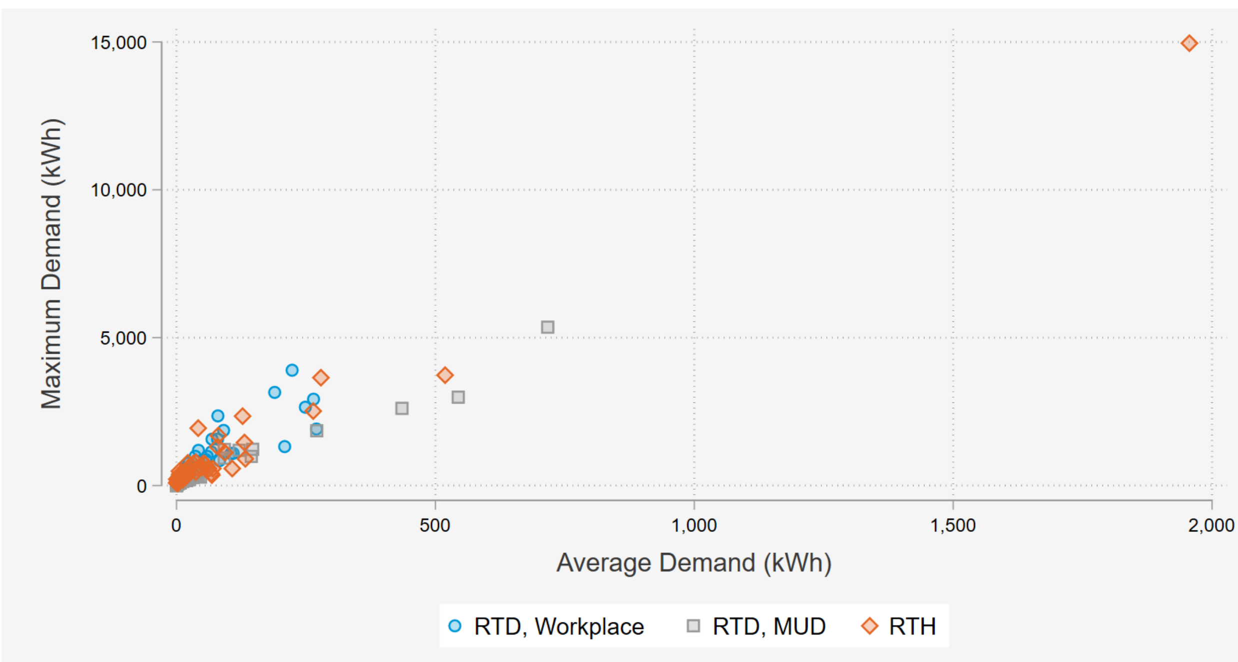
biased. The lack of price responsiveness is precisely estimated; we can rule out price elasticities below -0.016 based on the coefficient estimate and standard error in column (4).

Table 8: Estimated Elasticities (%) for PY 2022 -2024 Combined

	(1) Rate-to-Driver Workplace	(2) Rate-to-Driver MUD	(3) Rate-to-Host	(4) Rate-to-Host Omit Largest
ln(Price)	-0.346***	-0.248***	0.0607**	0.0442
	(0.0607)	(0.0357)	(0.0256)	(0.0299)
Observations	2,417,004	2,102,976	1,317,546	1,291,245
Sites	92	80	51	50
Pseudo-R-Squared	0.7408	0.7535	0.8667	0.7402

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 2024. 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



6.3 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 9. This table reports coefficient estimates and standard errors from four separate Poisson regressions. The specification is identical to that in Equation 3 but we interact $\log{(Price)}_{it}$ 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 9: Estimated Elasticity (%) by Event Type

	(1) Rate-to-Driver Workplace	(2) Rate-to-Driver MUD	(3) Rate-to-Host	(4) Rate-to-Host Omit Largest
ln(Price) x No Event	-0.340***	-0.228***	0.0737***	0.0517
	(0.0606)	(0.0466)	(0.0284)	(0.0331)
ln(Price) x Local Event	-0.344***	-0.239***	0.0560**	0.0482
	(0.0620)	(0.0413)	(0.0223)	(0.0300)
ln(Price) x System Event	-0.323	-0.318	0.567***	0.491***
	(0.210)	(0.554)	(0.167)	(0.153)
ln(Price) x Both Events	-0.403***	-0.389***	0.0669	-0.0552
	(0.0859)	(0.0801)	(0.0901)	(0.0591)
Observations	2,417,004	2,102,976	1,317,546	1,291,245
Sites	92	80	51	50
Pseudo-R-Squared	0.7408	0.7535	0.8668	0.7402

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 2024. 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.

7 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 26% 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:

- **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.
- **Estimate load shift that occurred under the VGI rate using a customer's otherwise applicable rate or a revenue-neutral flat rate.** The price elasticities estimated in this analysis can be used to predict consumption under alternative prices. We began to investigate this approach this evaluation season, and hope to continue next year. There are challenges associated with comparing rates across customer classes. An alternative approach would be to predict counterfactual consumption under a TOU rate or TOU-CPP rate that is constructed to recover the same revenue.
- **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.

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.

8 APPENDIX

Table presents local- and system-event impacts in kW for the average site for each site type for program year 2024 (October 1 2022 through September 30 2024). The table includes estimated coefficients 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). On average, rate-to-driver workplace sites delivered load reductions of 12.86kW during local event hours and 20.57 kW during system event hours. On average, rate-to-driver MUD sites delivered load reductions of 6.83 kW during local event hours and 9.13 kW during system events hours. The local event impacts are statistically indistinguishable from zero and differ to the estimates for the pooled program year 2022-2024 event impacts in the main analysis above. System event impacts are statistically significant at the 1% level for only rate-to-driver, workplace sites. This likely occurs due to system events being called

Column (3) reports estimated coefficients and standard errors for rate-to-host sites where charging is free at the site for drivers and the VGI rate is paid by the site host. As in our main analysis above, we find the estimated impacts for rate-to-host sites are statistically indistinguishable from zero.

Table 9: Event Load Impacts (kW) for PY 2024

	(1) Rate-to-Driver Workplace	(2) Rate-to-Driver MUD	(3) Rate-to-Host
Local Event Hour	-12.86	-6.828	-0.592
	(9.693)	(5.831)	(32.67)
System Event Hour	-20.57***	-9.127	3.519
	(6.798)	(7.160)	(22.47)
Local and System Event Hour	0.994	-6.206	120.4
	(13.84)	(10.56)	(112.1)
Event Anticipation Hour	0.463	3.791	-8.533
	(3.386)	(2.979)	(9.975)
Event Rebound Hour	1.892	2.983	9.946
	(3.550)	(2.641)	(8.154)
Observations	808,036	701,680	441,670
Sites	92	80	51
Avg. kWh	49.985	60.501	117.250
Avg. DAM Event kWh	37.605	7.795	
Avg. System Event kWh	23.537	73.018	99.364
Adj R-Squared	0.3677	0.6093	0.3136
Adj Within R-Squared	0.0005	0.0003	0.0000
Avg. Local Event kWh			236.803

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. This table reports coefficient estimates and standard errors from three separate OLS regressions. All regressions are estimated using site-by-hour observations for October 1 2022 through September 30 2024. 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.

Table 10 presents local- and system-event impacts in relative (%) terms for the average site for each site type for program year 2024. 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). On average, rate-to-driver workplace sites delivered load reductions of 55.2% during local event hours and 68.9% during system event hours. On average, rate-to-driver MUD sites delivered load reductions of 87.8% during local event hours and 23.3% during system events hours. The local event impacts are statistically significant at the 1% level but differ to the estimates for the pooled program year 2022-2024 event impacts in the main analysis above. System event impacts are statistically significant at the 1% level.

Table 10: Event Load Impacts (%) for PY 2024

	(1) Rate-to-Driver Workplace	(2) Rate-to-Driver MUD	(3) Rate-to-Host
Local Event Hour	-0.552***	-0.878***	0.0593
	(0.192)	(0.107)	(0.0700)
System Event Hour	-0.689***	-0.233**	0.170***
	(0.106)	(0.0996)	(0.0496)
Local and System Event Hour	0.0911	0.350	-0.0536
	(0.0974)	(0.226)	(0.0878)
Event Anticipation Hour	-0.113***	0.0288	0.0453
	(0.0417)	(0.0349)	(0.0403)
Event Rebound Hour	0.00189	-0.00906	0.0349
	(0.0559)	(0.0393)	(0.0341)
Observations	808,036	692,897	432,887
Sites	92	80	51
Pseudo-R-Squared	0.7750	0.7956	0.8744

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 2022 through September 30 2023. 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 rate-to-host site. Fixed effects in column (3) are interacted with MUD/workplace status.

Figure 22 and Figure 23 show estimates of average hourly site-level impacts at rate-to-host sites for local events and system events, respectively. These coefficient estimates, confidence intervals, and load shapes, are from Equation 1 estimated on rate-to-host 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 6 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.[12] For local event impacts shown in Figure 22, every hour is represented because for every hour there exists at least one event in the sample that included that hour. For system events, no events were called between midnight and 6 AM, so we do not report estimates for those hours. Examining these graphs, reductions are generally not statistically significant. This is unsurprising as rate-to-host sites did not yield statistically significant load impacts for the average event hour.

[12] 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 22: Local Event Estimated Average Hourly-Level Impacts for Rate-to-Host Sites

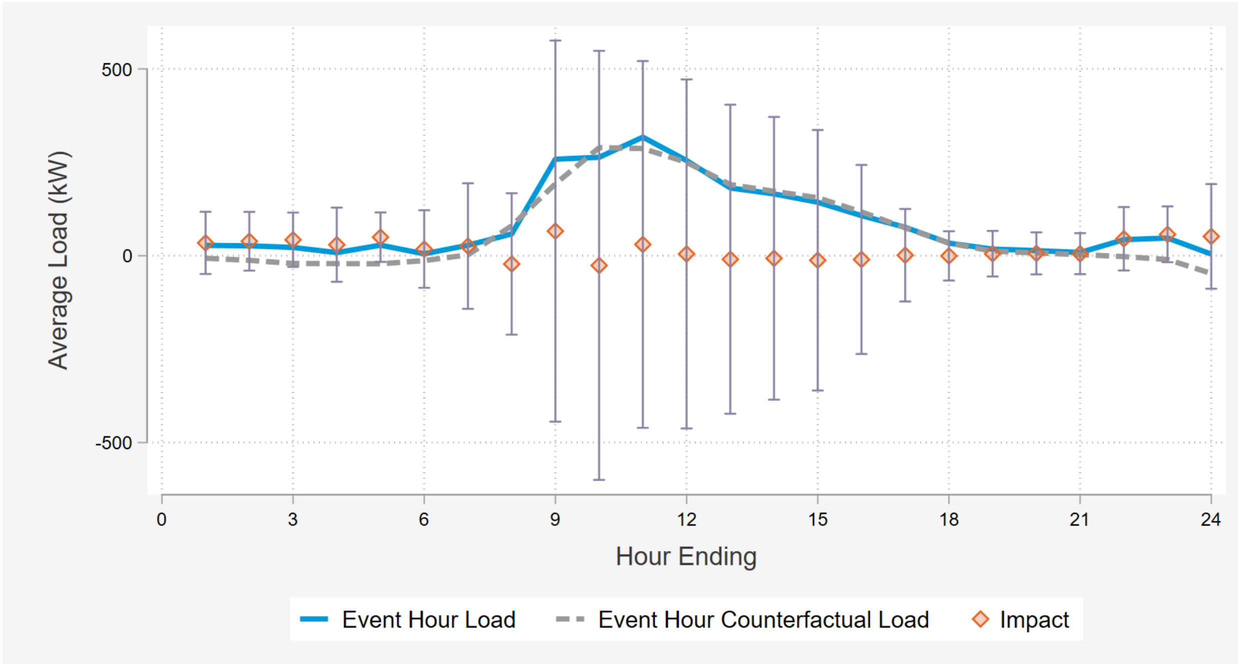
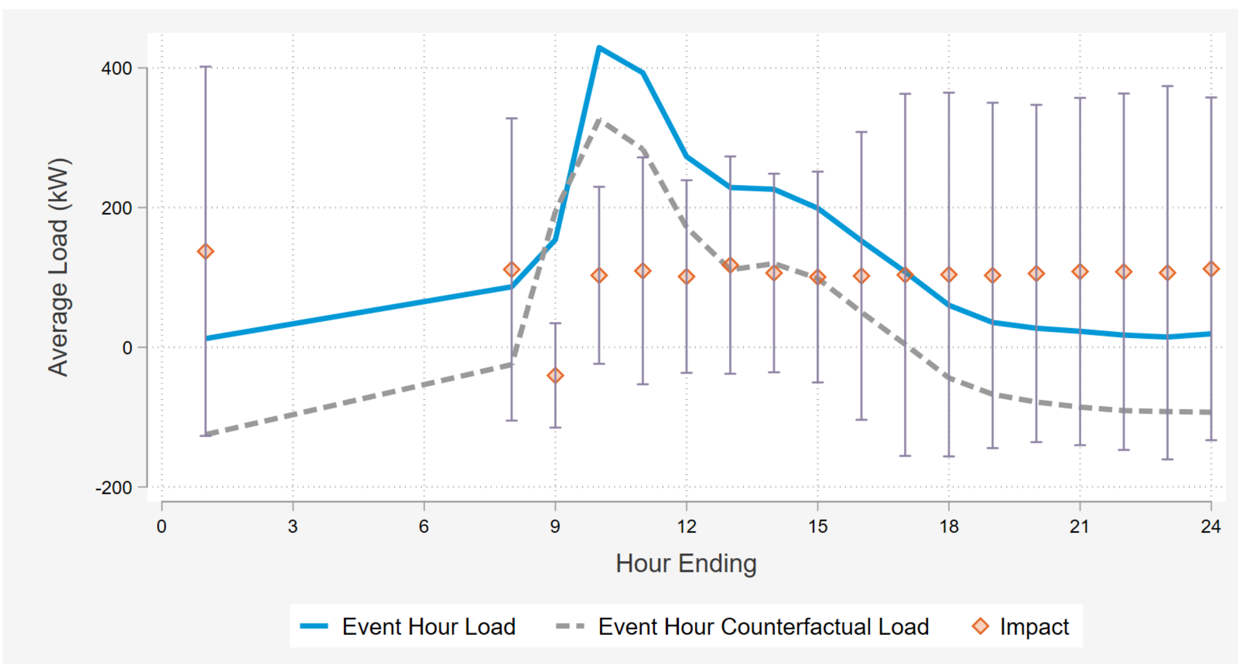


Figure 23: System Event Estimated Average Hourly-Level Impacts for Rate-to-Host Sites



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