Fast Chargers, Sluggish Responses: Competition in the Electric Vehicle Fast Charging Market

Josh Aarons

3/5/26

Abstract

Fast charging stations are considered crucial to hastening electric vehicle adoption and reducing emissions, but due to a lack of data, there has been little research on competition or consumer behavior. I compile novel price and quantity data to study the effect of fast charging station openings on incumbent station charging quantities and prices. I implement a difference in differences design that leverages the timing of nearby station entry. I find that incumbent stations' quantities and prices are largely unresponsive to competitor entry, but that following the entry of another station owned by the same network, charging decreases significantly and stations lower prices by around 7.5% of price margins. My price results contrast with the retail gasoline market, where new station entry brings down prices at competing incumbents but not stations under the same ownership. These differences may be due to both charging station capacity constraints and high market segmentation from charging networks' use of proprietary mobile applications and subscription plans. My results suggest policies aimed at reducing search frictions (such as price posting regulation) could increase the consumer benefits of current charging station subsidy programs.

1 Introduction

One government tool for lowering prices is increasing the number of competing firms, either through encouraging market entry or splitting up monopolists. In most standard economic models, the entry of new firms into a market reduces market power, decreases prices toward marginal costs, and increases social surplus. However, this outcome is not universal. More competition could have no effect due to supply-side frictions such as monitoring costs or pricing strategies (Arcidiacono et al., 2020) or even raise prices if increased competition leads to improvements in quality or capacity (Joskow, 1980). Recent research has tried to answer this question empirically and found differing results across industries (Arcidiacono et al., 2020; Davis, McRae and Seira, 2025; Taylor and Muehlegger, 2025; Busso and Galiani, 2019). In emerging markets such as the electric vehicle fast charging market, it is unclear how increased competition will impact the prices consumers face. Governments may be unable to reduce prices in these markets by increasing competition and may need to utilize other tools.

In this paper, I measure the impact of market entry on price competition in the electric vehicle fast charging market. The United States federal government and state governments have spent billions of dollars subsidizing electric vehicles (EVs) and charging infrastructure. Recent federal government efforts have focused on increasing provision of direct current (DC) fast charging (DCFC) stations. Unlike home or workplace charging, which are characterized by slow speeds (4-50 hours for a full charge depending on the charger type), fast charging provides the ability to recharge a car in under an hour, but comes at a premium price reflecting a large markup over the marginal cost of electricity. The average cost per mile of fueling using fast charging is higher than the cost per mile using gas in most states despite the general assumption that driving an EV is cheaper than a gas-powered vehicle.[1] If consumers care about input prices, high prices may reduce EV purchases. Households living in multifamily dwellings will face much greater costs of EV adoption as they are less likely to be able to charge at home. EV adoption has been relatively low for these households, so as the focus shifts to demographics with lower uptake, high fast charging prices may be an important barrier to fleet-electrification targets.

One barrier to research on charger pricing is the lack of data. No laws require existing stations to post prices in any systematic way or make them accessible via an API and most networks only post prices on their own mobile applications.[2] Asensio et al. (2025) find that

[1] This is a comparison of new vehicles with average efficiency and average fuel costs taken from the *New York Times's* analysis of Paren's charging price data.

[2] The National Electric Vehicle Infrastructure program mandates data reporting for stations receiving funding. However, the program has suffered from a slow rollout and only a small share of existing stations

only 34.4% of DCFC stations and 18.6% of chargers located along six major U.S. highways reported real-time data on PlugShare, the most complete third-party database. I address this data scarcity problem by collecting data from different sources and compiling a weekly panel of hourly prices at stations operated by Tesla, EVgo, and Electrify America, the three networks with the most DCFC chargers in California. This panel includes 15 months of weekly price data for around 75% of stations in California with multiple chargers and 85% of those chargers.[3] I match station data to three years of station-level electricity consumption data from Pacific Gas & Electric Company, the largest electric utility in California and a weekly measure of station quality. Using this data, I am able to delve into whether stations respond to increased competition by changing price or quality and how drivers respond to station entry.

I start by characterizing the fast charging market and presenting descriptive evidence of relatively static prices over time. I then measure price, quality, and quantity responses to market entry. I find that market entry does not affect the amount of charging at nearby competing stations, but does divert some charging activity from local stations owned by the entering station's network. Without a demand response, stations have no incentive to lower prices. I estimate that entry does not affect local competitor prices and can rule out price decreases larger than \$0.03/kWh in response to competitor market entry. I also find no evidence that station reliability responds to market entry. Taken together, these results suggest that charging stations do not respond to competitor entry by altering price or quality.

I contribute to two literatures. The first is the literature on market entry. I find at most small competitor price responses. My estimates of price decreases as a fraction of margins are smaller than those documented by Davis, McRae and Seira (2025) and Taylor and Muehlegger (2025) in the retail gasoline market. Arcidiacono et al. (2020) also find no effect of entry on prices. However, they find a negative impact on retail volumes. In contrast, EV drivers in California respond very little in aggregate to new competing station entry. Drivers show a much larger response to entry of a station owned by the same network as a nearby incumbent, suggesting they are much more likely to shift charging within network than across networks. This set of results points to demand-side frictions, rather than the supply-side frictions noted by Arcidiacono et al. (2020), may explain the lack of price response in the fast-charging market.

The second literature I contribute to is the literature on EV charging. I show that stations apply large markups to electricity prices and there is little price competition between stations

have received funding from the program. Though the law was signed into effect in November 2021, California first awarded funds from this program in December 2024.

[3]There are a number of single plug stations that companies install for local businesses. The speed and quality of these stations tends to be lower than at more traditional stations.

regardless of plug type. Others have estimated the effect of station deployment on EV purchases (Li, 2023; Remmy, forthcoming; Cole et al., 2023; Springel, 2021; Li et al., 2017), but no work has measured charging market price dynamics. I show that competitor entry does not meaningfully reduce prices, but own-network entry does reduce prices through relieving incumbent capacity constraints. Additionally, I show that entrants are much more likely to pull charging volumes away from nearby competitors using the same charging standard if the two stations are owned by the same network. This suggests that market segmentation may be achieved through subscriptions or proprietary apps rather than only different charging standards. This is particularly relevant for work on the potential benefits of standardizing plug types (Springel, 2021; Li, 2023).

The paper proceeds as follows. Section 2 provides information on DC fast charging and the literatures on EV charging and market entry. In Section 3, I describe the data I use in this paper and how it was collected. In Section 4, I present my empirical design. I provide results in Section 5. Section 6 concludes.

2 Background

2.1 Fast Charging

2.2 Competitive Responses to Entry

In standard models of firm price competition, an increased number of firms in the market leads to lower prices. However, incorporating search costs or competition on non-price dimensions can suggest prices will increase. Satterthwaite (1979) explains that when the efficiency of searching for information on suppliers decreases due to market entry, consumers become less price elastic, allowing sellers to raise prices. Joskow (1980) shows that when hospitals face more competition, they increase quality to attract customers (who search on quality rather than price), but doing so is costly and leads to higher prices. Other pricing or search frictions can also create situations where an increase in competition does not have any effect on prices.

Due to the uncertainty from theoretical work about how prices will respond to increased competition, Arcidiacono et al. (2020) advocate for the role of empirical work. They study the impact of Walmart supercenter entry on grocery prices at nearby competitors. They find no effect on prices even though the incumbent stores experience a decrease in sales. They suggest that monitoring costs may prevent incumbents from adjusting prices in response to entry. Davis, McRae and Seira (2025) study the impact of new retail gasoline stations in Mexico on prices and quality at nearby incumbents. They find that entry leads to a decrease

in prices at nearby incumbents equivalent to 6% of margins. They find no effect on price for incumbents owned by the same firm as the entrant. Taylor and Muehlegger (2025) find similar results in California: incumbents decrease prices by 7% of markups in response to entry. They also find that exit has no impact on price, possibly because exit occurs in highly competitive markets and the firms that exit tend to have lower quantities. Studying gas station entry in Spain, Bernardo (2018) finds a larger impact than Davis, McRae and Seira (2025) and Taylor and Muehlegger (2025) do. Busso and Galiani (2019) uses a randomized control trial in the Dominican Republic and finds that entry in the retail sector reduces prices by 2-6% and improves service quality.

Overall, the results of the empirical literature show prices often decrease in response to entry, but that this varies by industry and setting. The fast charging market is ostensibly similar to the retail gasoline market, as both sell a commodity input used to power vehicles. However, the lack of price posting regulation, longer refueling times, and consumers' concerns and lack of information about charger quality (Asensio et al., 2025) may lead charging stations to be less responsive to competition than gas stations. Additionally, stations have fairly rigid pricing strategies. Electrify America and EVgo both choose each station's price from a relatively small menu of prices they use throughout California. Further, stations update their prices infrequently. Tesla and EVgo change prices only once every several weeks and Electrify America updates even less often.

2.2.1 Fast Charging Stations

Electric vehicle charging is generally classified into three levels based on speed. Level 1 and level 2 charging both use alternating current (AC), which limits the power output. Level 1 charging refers to any plug that connects to a standard 120 volt AC outlet and produces a power output of 1 kW. Recharging a 60 kWh battery[4] to 80%[5] would take 40-50 hours with level 1 charging, so it is only practical for home charging (USDOT, 2023). Level 2 chargers, 7-19 kW, can replenish a 60 kWh battery in 4-10 hours, and can provide 10-20 miles of range in an hour. As a result, level 2 chargers are often installed at workplaces, retail, and homes (though this is not always possible). Though they are faster than level 1 chargers, they face the same problem that they cannot quickly fuel an EV to drive for multiple days and therefore may only address charging concerns for drivers with consistent access.

Level 3 charging uses direct current (DC) to provide much more power (50-500 kW). Level 3 charging is more often called DC fast charging, a nomenclature I will use throughout this

[4] 60 kWh is the battery capacity the U.S. Department of Transportation uses as an example and the capacity of the base version of the Tesla Y, currently the most common EV in the United States.

[5] Above 80%, charging speed slows.

Charger Level	Typical Power Output	Estimated BEV Charge Time	Estimated Electric Range per Hour of Charging	Typical Location
Level 1	1 kW	40-50 hours	2-5 miles	Home
Level 2	7-19 kW	4-10 hours	10-20 miles	Home, Workplace, and Public
DC Fast Charging	50-350 kW	20 min - 1 hour	180-240 miles	Public

Notes: Source: U.S. Department of Transportation.
Charge time is calculated assuming a 60-kWh battery. Most of the EV models popular in the U.S. have battery capacities around 60-80 kWh.

paper. DC fast chargers (DCFCs) can provide 180-240 miles of range in an hour. Therefore, they are generally considered the infrastructure necessary to enable longer trips and provide regular refueling to those who cannot charge at home or work. DCFCs have much higher installation costs than level 1 and level 2 chargers. Gamage, Tal and Jenn (2023) study 36 DCFC installation sites along transportation corridors and find costs ranging from $122,000 to $440,000 per charger, though they note that the existing literature has estimated lower costs ($20,000-$150,000). Their study also highlights the time cost of installations; interviewees said projects took longer than anticipated and suggested a 4- to 6-month precautionary lead-time to begin working with electric utilities.

A growing literature studies the interaction between charging station infrastructure and EV ownership. Prior work shows that increasing charging infrastructure leads to more EV purchases (Cole et al., 2023; Springel, 2021; Li et al., 2017; Sommer and Vance, 2021; Zhou and Li, 2018) and that subsidizing charging stations is more efficient for encouraging EV adoption than subsidizing vehicle purchases (Cole et al., 2023; Springel, 2021; Li et al., 2017). Remmy (forthcoming) finds that EV station subsidies in Germany are less efficient at inducing EV purchases, but do not prompt car retailers to shift to selling shorter range EVs as direct vehicle subsidies do. Li (2023) differentiates between charging standards for DCFCs and includes strategic deployment of charging stations in her model. She finds that the lack of a uniform charging standard decreases EV adoption.

Recent work has started to look at how consumers respond to charging prices. Garg et al. (2025) implement a randomized control trial using workplace chargers to test the impact of nudges on charging behavior. They find that drivers respond to discounts by increasing the amount of time they spend charging (though there is no impact on the number of charging sessions) and estimate an elasticity of -0.44. Bernard et al. (2025) use an experiment in the United Kingdom to estimate the impact of public charging prices on usage. They find a large impact of price on short-run charging demand and estimate elasticities of -1 to -1.45

for public charger use. Roughly half of the stations in their data have charging power of 50 kW or greater, the speed I focus on in this paper. Bernard et al. (2025) run their experiment using a mobile application that covers more than 100 charging networks and 60% of public chargers in the country. This is notably different from the U.S. context, where drivers must use different apps to compare prices.

2.2.2 The Fast Charging Market

The fast charging market in California is highly concentrated. Three networks, Tesla, EVgo, and Electrify America, operate 75% of stations with multiple chargers. Tesla, the largest network, builds larger stations than nearly all other networks; it operates 33% of all stations with multiple chargers and 63% of chargers at these stations. Some large networks segment the market through only listing prices on their own mobile applications. Neither Tesla nor Electrify America allow PlugShare, the largest aggregator of EV charger information, to access and post their prices or real-time information on charger availability.

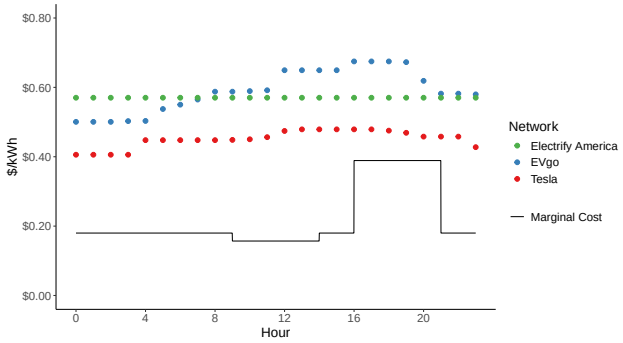
Another key way that stations have segmented the market is through differences in charging standards. Unlike level 1 and level 2 charging, which both use the same type of charging plug, DC fast chargers have been developed with three different charging standards.[6] All Teslas and Tesla charging stations exclusively use Tesla's charging plug, the North American Charging System (NACS). Until 2025, no other cars came equipped with the ability to charge at Tesla stations and instead were equipped for either CCS (also called J1772 combo) or CHAdeMO plugs. Further, other stations did not offer NACS charging until 2025. Automakers sell adapters to allow owners to charge at stations with different charging standards, development of these adapters as has been slow and even as of early 2025, most non-Tesla owners were unable to charge at the limited number of Tesla stations the company had made available to drivers of other EVs.

High fixed costs and market concentration have fostered a market defined by large markups. Section 2.2.2 shows networks' average hourly prices at DCFC stations served by PG&E during August and September 2024. The black line on the figure represents the marginal cost of a kWh of electricity at the majority of stations based on the most used electricity rates during this period.[7] Comparing the average prices and the prevailing marginal cost, it is clear that markups greater than 100% of marginal cost are common. In fact, fueling an EV at the average EVgo afternoon or early evening price was slightly more expensive

[6] For more on the history of charging standard differences and the consequences for EV adoption, see Li (2023).

[7] Smaller stations were more likely to use the lower capacity rates, which were within $0.02/kWh of the black line at all hours.

per mile than driving an average efficiency new gas powered vehicle at California's average gas cost at the time of $4.50/gallon.



Notes: Data is for August-September 2024. Prices are averaged across all stations operated by each network in PG&E's service area. Marginal cost is the per kWh electricity cost under the most frequently used electricity rates.

Figure 1: Average Hourly Prices and Marginal Costs at DCFC Stations in PG&E Service Area

3 Data

3.1 Price Data

My price data is a weekly panel of hourly station prices in California. Each week, a team of research assistants and I collected hourly prices for each Tesla, EVgo, and Electrify America DCFC station. Data comes from each company's mobile app and PlugShare, a third party aggregator of charging station data, which posts EVgo prices. The collection period ran from Saturday to Friday each week. The list of stations comes from querying the Alternative Fueling Station Location API from the DOE's Alternative Fuels Data Center each Saturday. The Alternative Fueling Station Location data contains information on station location, opening date, charging network, and the number and type of chargers at the station. Since prices could be collected any day between Saturday and Friday, weekly prices do not necessarily reflect price changes from that week. The panel covers July 2024 through December 2025,[8] though the first 10 weeks were limited to stations in Southern California.

Networks do not necessarily offer the same price to all consumers. For example, EVgo offers multiple subscription plans that lower volumetric prices in return for a monthly fee.

[8]Data collection is ongoing.

Tesla has only opened some of its stations to drivers of non-Teslas, but at those stations prices are 40% higher for charging non-Tesla vehicles (though this premium can be waived if one subscribes to a monthly plan they offer). I use the base cost from each network. This can therefore be viewed either as the base cost for a Tesla driver[9] or for a non-Tesla driver who subscribes to the $13.99/month Tesla plan that reduces their price to that faced by Tesla drivers. I do not include each network's fees for idling at the station after charging or Tesla's congestion fee for charging above 80% when stations are busy.

In total, the data include more than 1.8 million station-week-hour prices across 1,314 charging stations. Figure 2 shows that average weekly prices at 5PM by network at stations in PG&E's territory have not changed frequently.[10] Tesla updates prices more frequently than competitors. Though it is not visible in this figure, Tesla and EVgo have more pricing variation within day and across geographies than Electrify America. The two networks predominantly used time-of-use pricing that varies throughout the day for most of the sample period, but moved towards more uniform pricing in late 2025.

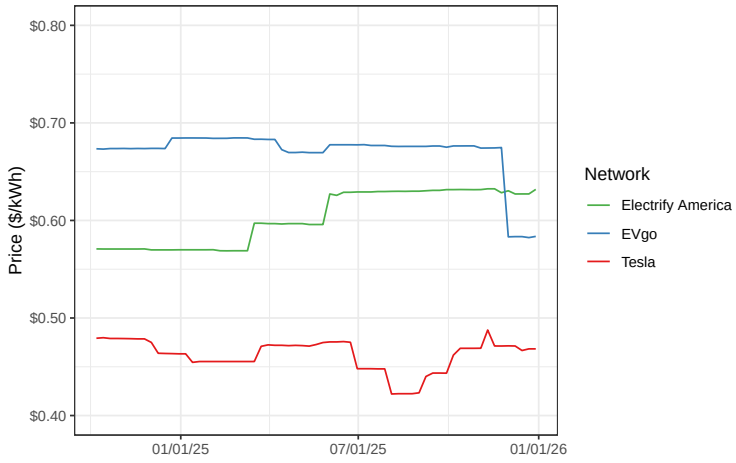


Figure 2: Average Weekly 5PM Prices by Network at Stations Served by PG&E

3.2 Electricity Utilization Data

I combine station characteristics and price data with station-level electricity consumption data from Pacific Gas & Electric Company (PG&E), the largest electric utility in California. The data covers 2022 through late 2024 and is available for DCFC stations that PG&E identified in their data or matched to addresses in the Alternative Fueling Station Location

[9]The median EV driver in California drives a Tesla since more than half of EVs registered in the state are Teslas.

[10]Appendix Figure 2 presents comparable figures for the San Diego and Los Angeles metropolitan areas to show that price change behavior has been similar across the state.

data. The data includes both electricity consumption measured in kWh, which I aggregate to the hourly level, and monthly billing amounts and rates. This data allows me to measure hourly quantities and marginal costs at 443 stations that do not share meters with another station.

3.3 Station Quality Data

My last data source is a measure of quality from Paren, a charging station data company. Specifically, I use Paren's Station Health Score, a weekly index of station quality. The score is calculated using a proprietary algorithm that incorporates a charger's uptime and share of charging attempts that were successful during the past week. A Station Health Score (referred to as health index for the remainder of the paper) of 100 during a week would indicate that the station was operational the whole week and all customers that attempted to initiate a charge at the station did so successfully. Paren's data covers all EVgo and Electrify America stations throughout the sample period, but only began to cover the majority of Tesla stations in 2025. Paren provides data on a number of other charging station characteristics, and began collecting price data in 2025. Using their September 2025 price data, I match my station-week-hour price data with their price data and find that more than 99% of station week-hour prices at EVgo and Electrify America stations that month match across the two datasets. At the subset of Tesla stations for which they collected price data, my data matched theirs for 98% of station week-hour prices.

Table 1: Summary Statistics

	Tesla	EVgo	Electrify America	Other
All California				
Stations	637	495	291	1815
Plugs per station	16.4	4.4	4.9	2.8
Price	\$0.43	\$0.60	\$0.61	
Health index	96.0	77.8	92.4	72.7
Entered since 08/2024	26%	20%	5%	29%
Stations within 5 minutes	2.5	3.0	2.3	3.9
Chargers within 5 minutes	15.6	20.4	18.8	18.0
Electricity Use Data				
Stations	198	123	108	68
Plugs per station	15.4	4.6	4.6	5.9
Price	\$0.43	\$0.60	\$0.60	
Health index	97.2	78.8	91.7	79.3
Daily kWh	5151.7	769.3	1566.6	275.1
Stations within 5 minutes	1.5	2.4	1.4	3.3
Chargers within 5 minutes	9.2	13.9	11.3	14.8

4 Empirical Design

I measure responses to market entry by exploiting the exact timing of entry. Networks choose new locations based on market conditions, but the licensing and infrastructure upgrade process takes several months and is subject to a large amount of variation in how long it takes. Once operational, stations have no reason to delay opening as the operational costs are below their expected revenues and they want to recover fixed costs. This means that the exact timing of entry is determined by administrative and technical factors rather than market conditions. The identifying assumption, that stations do not control the exact timing of entry, is the same as that used in Arcidiacono et al. (2020), Davis, McRae and Seira (2025), and Taylor and Muehlegger (2025), and the models I use are similar to those in Davis, McRae and Seira (2025).

4.1 Difference in Differences

My primary empirical approach uses a staggered difference in differences model. As in Davis, McRae and Seira (2025), I exploit variation in the number of nearby stations due to the entry and exit of stations. This model is distinct from traditional difference in differences models in that treatment is measured as an increase in the number of nearby stations rather than as a binary variable. Before a new station opens, a nearby station faces N competitors, but after the opening, it faces $N+1$ competitors. Estimating the difference in outcomes before and after entry across all stations recovers the causal effect of an additional competitor. Specifically, I estimate the following model:

$$\begin{aligned} y_{ihw} =& \beta_1 N[\text{Same Network}]_{ihw} + \beta_2 N[\text{Dif. Network, Dif. Plug Type}]_{ihw} + \\ & \beta_3 N[\text{Dif. Network, Same Plug Type}]_{ihw} + \mu_{ih} + \gamma_{wu} + \varepsilon_{ihw} \end{aligned}$$

where N is the number of stations within a five-minute drive. I differentiate between stations owned by the same network as station i and those owned by different networks. For stations owned by different networks, I further differentiate between those that use the same plug type as station i and those that use a different plug type.

I consider price, health index, and electricity usage as outcomes. When I estimate price, I use data at the station-week-hour level. This allows me to account for different prices over the course of the day. I include station-hour fixed effects, μ_{ih}, to control for time-invariant station characteristics and week-utility fixed effects, γ_{wu}, to control for time-varying factors such as demand and electricity rates. For the estimation of health index, I use weekly data

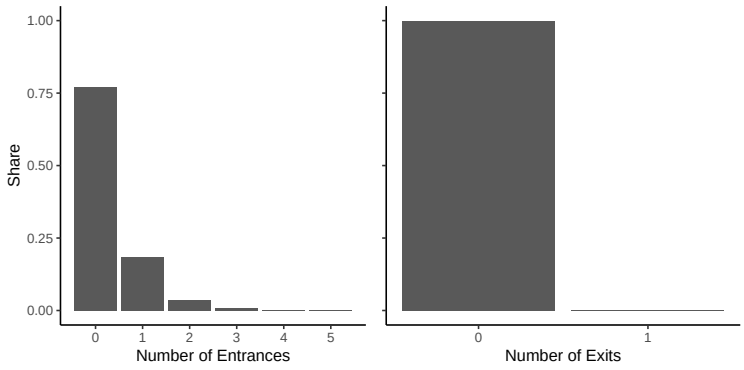


Figure 3: Frequency of Number of Entries and Exits Experienced by Incumbents

and therefore include station fixed effects instead of station-hour fixed effects. For electricity usage, I use daily data and include station fixed effects and day-utility fixed effects.

This model identifies the β coefficients by using within-station variation in the number of nearby stations. Figure 3 shows that exits are very rare in the data, and variation in number of nearby station comes almost entirely from station entry. The week-utility fixed effects account for potential variation that comes from temporal trends across stations not exposed to a change in the number of nearby stations. These fixed effects are estimated using both stations that experienced a nearby entry during the sample period and stations that did not. These never treated stations provide a control not impacted by entry during any week and improve the precision of the fixed effects estimates. I also provide results using just treated stations due to concerns that never treated stations do not experience the same market trends as treated stations. I apply two-way clustered standard errors at the CBSA and year-month level, since the probability of treatment varies across CBSAs and time. I do not interact CBSA with year-month because the error for one CBSA in a given month is likely correlated with the error the previous month (Colin Cameron and Miller, 2015). The total number of clusters ranges from 51 to 59 across analyses.

I consider a number of different specifications using this model. In my primary specification, I define all stations within a five minute drive of a station as "nearby". I also present results using distances of three and ten minutes in Section 6. Similar to distance, competitor station size is likely an important mediating factor. Around $\frac{1}{3}$ of all locations registered in the Alternative Fueling Station Location data only have a single charging stall, and just over half have fewer than four charging stalls. In my primary specification I use all charging stations, but I also run all models using only stations with four or more chargers in case stations are only responsive to nearby locations they believe can take away a notable share of their revenues. When estimating the effect of entry on incumbent charging quantities, I use the number of stations in my primary specification, but also consider the number of

charging plugs to incorporate station size in alternate specifications. To do this, I divide total station-level utilization by the number of charging plugs at the station to calculate the amount of charging per plug.

4.2 Event Study

In my context, where station construction is both public and slow, a key threat to causal identification is anticipation. If stations lower prices or change quality in anticipation of station entry, then I will overestimate the "pre-period" price, biasing the difference in differences estimate towards zero. I use an event study specification to show pretrends and test for threats to identification. I estimate the following equation:

$$y_{ihw} = \sum_{\tau=-8}^{\tau=8} \beta_\tau [\text{Event Week}_{ihw} = \tau] + \mu_{ih} + \gamma_{wu} + \varepsilon_{ihw} \tag{1}$$

where the event week variable ranges from eight weeks before entry to eight weeks after entry. I avoid overlapping treatment by restricting to only entrances near an incumbent without another nearby entrance within 16 weeks. The fixed effects are the same as in the difference in differences estimating equations. For the electricity usage outcome, I aggregate daily electricity consumption to the weekly level.[11] I use the same specifications as in the difference in differences model, except I run all models at the station-level (rather than per plug utilization).

Similar to the difference in differences model, I include untreated stations to improve estimation of the temporal fixed effects. Unlike that model, stations that experience a nearby opening drop out of the sample eight weeks after treatment. This creates a situation where fixed effects are estimated on an increasingly selected sample as time passes. Therefore, I predominantly use this model to test for evidence of pretrends and use the difference in differences model for estimating the effects of entry.

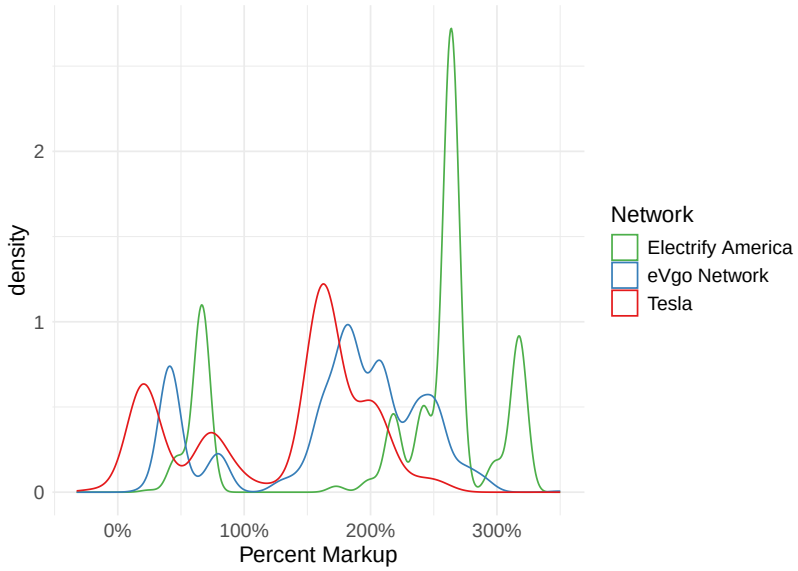
5 Results

5.1 Markups

DCFC stations apply consistently high markups. Figure 4 shows the distribution of markups across all station-week-hours for stations served by PG&E. For this figure, I assume

[11] In this equation, the event week is defined as the number of full weeks since opening.

all stations choose the rates with the lowest marginal cost as this is the most common choice I observe in the billing data.[12] During the sample period, median and mean markups are above 100%, meaning that the cost of driving an EV using fast charging is well above the marginal cost of electricity.



Notes: Markups are calculated as $\frac{(\text{p-MC})}{\text{MC}}$ where MC is the most commonly used marginal cost of electricity by charging stations served by PG&E.

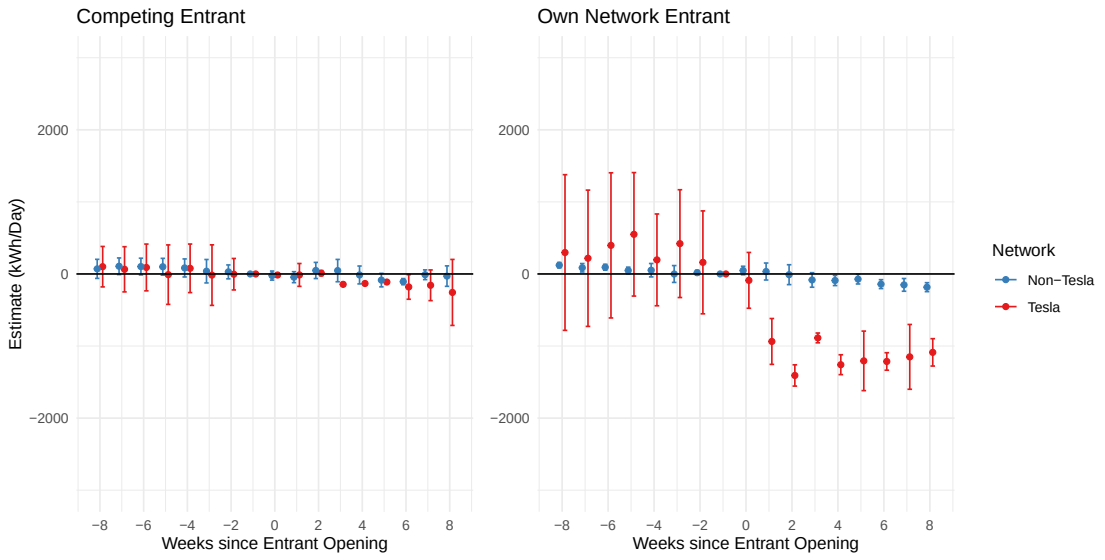
Figure 4: Distribution of Markups

5.2 Charging Quantities

I present the results for station utilization from the primary event study specification in Figure 5. The figure shows that there are no pretrends in electricity use at incumbent stations near entrants. There is no effect of competitor market entry on charging activity at nearby stations; however, there is a negative effect on charging activity at nearby stations operated by the same network for non-Tesla stations. Tesla stations see a large, but not statistically significant, decrease in use following the opening of another Tesla station nearby. The charging decreases appear to be fully realized within two weeks of entry and continue for the remainder of the eight-week event study window, suggesting entry may permanently reallocate charging activity.

I estimate the effect size of entry using the difference in differences model and considering a number of specifications. I separate Tesla and non-Tesla stations because the primary (and

[12]This figure will be updated in the future with a version calculated using only data for which I observe the actual marginal cost of electricity the station pays.



Notes: Data is for total electricity consumption at each station and spans January 2022 - August 2024.

Figure 5: Event Study Estimates of Station Entry within Five Minutes on Incumbent Daily Electricity Consumption

only) charging standard used at Tesla stations (NACS) is different from the primary charging standard used at non-Tesla stations (CCS). This means that entry of a station using the same charging standard for an incumbent EVgo station most commonly means a new non-Tesla station, while the entry of a station using a different charging standard means a new Tesla station. For Tesla, entrants with the same standard are newer stations from competitors that have incorporated NACS charging plugs.

Table 2 shows results similar to those in the event study plots. Station entry reduces charging activity at nearby stations also operated by the entrant's network. This effect is large in magnitude – Tesla incumbents within a five-minute drive of Tesla entrants experience daily charging volumes 1,504 kWh lower after entry than before. This effect is equivalent to more than 30 fewer cars recharging from 20% to 80%. For non-Tesla stations, a new own-network station opening nearby decreases charging volumes by 353 kWh. The difference in magnitude is largely explained by the difference in average station size – Tesla stations in the data have three times as many chargers as non-Tesla stations on average.

Competing station entry has a much weaker effect on incumbent charging. Entry of new stations using a different charging standard has no effect on incumbent quantities. This makes sense since drivers are unlikely to switch to a station with a different charging standard. Entry of competing stations using the same charging standard as incumbent non-Tesla chargers does decrease charging quantities by 59 kWh per day, around one-sixth the

	Own Network	Competitor Dif. Standard	Competitor Same Standard
Use (kWh/day)			
Tesla	-1851.8**	-128.5	95.1
	(279.1)	(814.0)	(253.6)
Non-Tesla	-352.7**	-49.4	-59.5**
	(84.9)	(315.9)	(13.5)
Price ($/kWh)			
Tesla	-0.017**	0.003*	0.005*
	(0.002)	(0.001)	(0.002)
Electrify America	-0.031**	-0.008	-0.001
	(0.001)	(0.006)	(0.001)
EVgo	0.001	-0.003	-0.001
	(0.002)	(0.003)	(0.001)
Quality (Health Score)			
Tesla	0.4	-0.1	0.3
	(0.4)	(0.5)	(0.2)
Electrify America	-0.6	-0.2	-1.0
	(0.7)	(0.6)	(0.5)
EVgo	1.1	-1.5	3.0*
	(6.7)	(2.1)	(0.9)

Table 2: Difference in Differences Results

Notes: */** denote significance at the $p < 0.05/0.01$ levels, respectively.
Standard errors are clustered at the CBSA and year-month level using two-way clustering.
Electricity use data span January 2022 - August 2024. Price and quality data span October 2024 - December 2025.

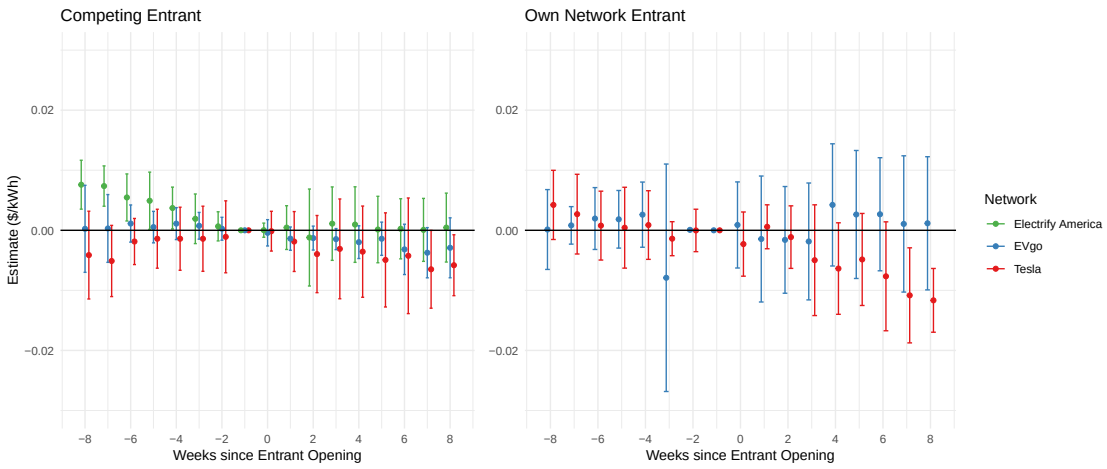
effect of a new own-network station. My estimate of Tesla incumbents' response to new competitors is neither statistically significant nor large in magnitude. The smaller responses to competitor entry are important for the literature on EV charging. Most work on charging standards has assumed that consumers will treat all stations on the same charging standard equivalently regardless of network, but this result suggests that consumers may instead have strong network preferences.

Despite the negative effect on nearby incumbents under the same ownership, new stations generally increase total fast charging activity in the entry area. During the first four weeks of operation, new Tesla stations average 4,312 kWh of charging per day while EVgo and Electrify America stations average 607 and 429 kWh/day, respectively (see Appendix Table 1). These quantities are much larger than the decreases associated with new station openings I estimate with the difference in differences model. Taken together, these results suggest that DCFC station openings increase the amount of fast charging in an area rather than reallocate charging. While this increase is likely due to reallocation from other charging sources such as home charging or slower public charging rather than more EV driving, my data do not provide information on quantities at other charging locations.

5.3 Prices

I disaggregate results by network because each employs different pricing strategies that impact both how frequently they change prices and by how much. Event study regressions shown in Figure 6 suggest that Tesla and EVgo do not change prices in anticipation of deployment of new stations, regardless of ownership. However, Electrify America prices do decrease by \$0.008 over the eight weeks before competitor entry, suggesting Electrify America may lower prices in anticipation of increased competition. This may bias results towards zero for the difference in differences estimate of price effects. The event study figure also shows that EVgo prices fall by around \$0.003 following competitor entry but do not change significantly following own-station entry. Tesla incumbents do not appear to adjust prices in response to competitor entry, but do decrease prices by around \$0.01 following own station entry.

I separate the results of the difference in differences model by incumbent network and entrant-incumbent charging standard match (whether they both use the same charging standard). The leftmost panel of Table 2 shows estimates for the impact of entrants on prices at own-network incumbent stations. Electrify America and Tesla stations reduce prices by 3.1 and 1.7 cents in response to own-network entry. These results are large – 7.6% and 7.5% of margins, respectively – and consistent across specifications.



Notes: Data is for station-week-hour prices and spans October 2024 - December 2025.

Figure 6: Event Study Estimates of Station Entry within Five Minutes on Incumbent Price

I estimate no effect of competitor entry on EVgo and Electrify America prices, regardless of charging standard. However, the event study analysis showed Electrify America appears to adjust prices in anticipation of competitor entry, which would bias the difference in differences estimate towards zero. Tesla prices increase slightly following the entry of competitors, with a larger effect for stations with plugs with the same charging standard as Tesla (0.5 cents) than those with a different standard (0.3 cents). One possible explanation for this counterintuitive result is that station entry leads to increased EV ownership ((Cole et al., 2023; Springel, 2021; Li et al., 2017)), which increases demand at Tesla stations. However, EV ownership is unlikely to respond so quickly, and it is more likely that these results are spurious. In fact, neither is robust to other specifications – both results are not significant in the model using the number of charging plugs rather than stations (see Appendix Figure 6) and are not significant for all specifications of the model using stations (see Appendix Figure 5).

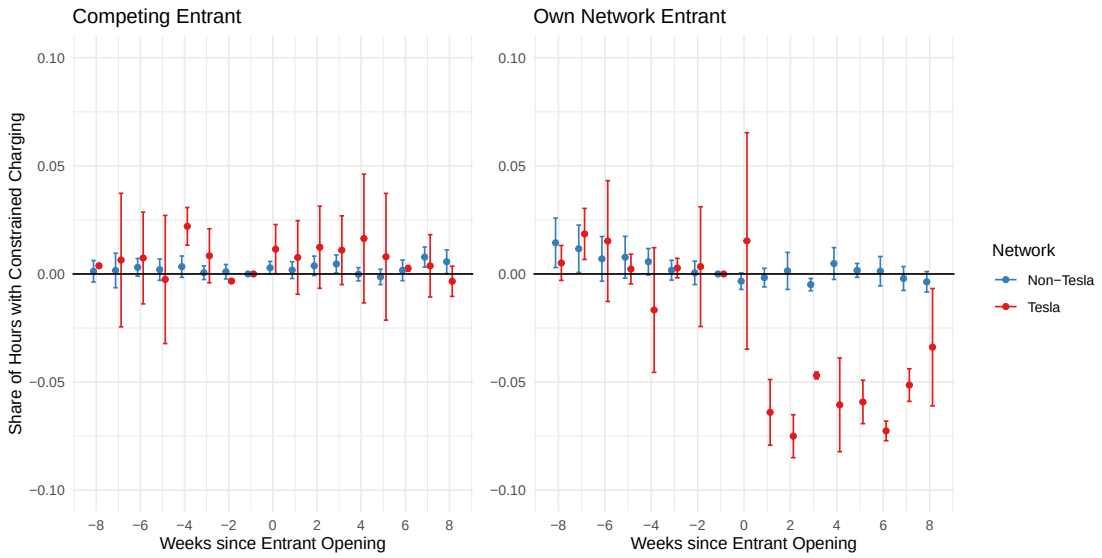
Overall, the results suggest minimal response to competitor entry. Under all models, EVgo and Electrify America do not change prices in response to competing entrants using a different charging standard. When I use the model using the number of charging plugs, I estimate that entry leads to a small reduction in price at nearby EVgo and Electrify America incumbents using the same charging standard. Across all models, I can rule out price responses greater than 11% of margins to competitor entry. Under my preferred model, I can rule out responses greater than 4.6% of margins, which is lower than the central estimates Davis, McRae and Seira (2025) and Taylor and Muehlegger (2025) find in retail gasoline markets.

Surprisingly, Tesla and Electrify America's price decreases following own-network entry

are 7.5% and 7.6% of margins, which are both the opposite sign and much larger than the results Davis, McRae and Seira (2025) find for same-owner gas station entry. One possible explanation is capacity constraints. Charging is slower than refueling a car, and charging a car from 20% to 80% (the standard metric for charging measurements) generally takes from 10 minutes to an hour depending on charging speed and battery size. As a result, drivers who show up to a full station are generally less likely to wait than drivers arriving at a full gas station. Networks have tried a variety of methods to reduce capacity constraints, including idling fees and limiting the battery level cars can charge to (charging gets increasingly slower as a battery charges from 80% to 100%). New stations relieve capacity constraints, allowing networks to sell more units of electricity, but do not change the marginal cost of electricity. The result is that the price-setting firm supplying a normal good lowers price as marginal cost and marginal revenue intersect at a greater quantity, which corresponds to a lower profit-maximizing price.

I check for empirical evidence that station openings near own-network incumbents relieve capacity constraints. Ideally I would define capacity as any hour where there is an instance that no chargers are available or the station must reduce the amount of electricity drawn by each charger. I cannot observe either in my data, so I calculate the maximum observed electricity usage during any given hour during the station's history and designate an hour as potentially capacity constrained if electricity consumption during that hour is at least 75% of the observed maximum. Using this definition, I classify around 0.9% of station hours as capacity constrained. I run the same models as in Section 5.2 but using the exceedance of 75% of the observed maximum as the outcome variable. I also limit to daylight hours, which I classify as 8 AM to 8 PM, as charger use is lower overnight.

The events study results in Figure 7 show that new own-network stations significantly reduce the likelihood of capacity constraints during daylight hours. The share of daylight hours where electricity consumption exceeded 75% of the station's peak observed consumption was 7.2 percentage points lower during the eight weeks following station entry than the eight weeks before for Tesla incumbents and 0.2 percentage points for non-Tesla stations, though there is a notable pretrend in the non-Tesla event study. These estimates are very large in magnitude, equivalent to a 63% and 33% decrease, respectively, from the average during the eight weeks before opening. This result strengthens the assertion that incumbent stations lower prices following nearby own-network entry since they are less likely to be capacity constrained.



Notes: Data is for total hourly electricity consumption at each station and spans January 2022 - August 2024.

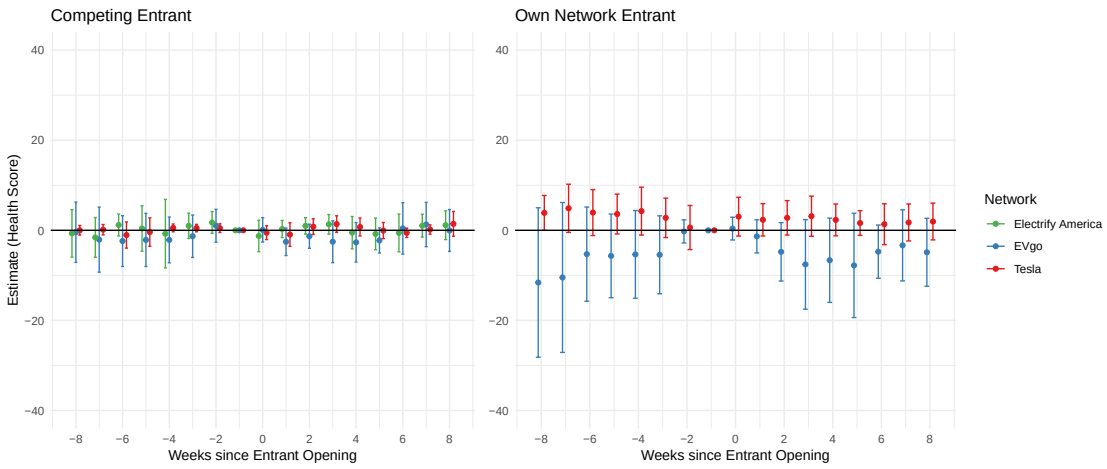
Figure 7: Event Study Estimates of Station Entry within Five Minutes on Share of Hours near Charging Capacity

5.4 Quality

I use Paren's Station health index as a measure of quality. On average, Tesla and Electrify America have high health scores at their stations (96.0 and 92.4 out of 100, respectively), while EVgo has a notably lower health score (77.8). This means that Tesla and Electrify America have less ability than EVgo to improve station health since the average health index score is already higher at their stations.

Figure 8 shows results from the event study model. None of the event study regressions suggest that station entry has an impact on incumbent station health. However, there does appear to be a potential slight improvement in health preceding entry of EVgo stations, with quality falling again after the week of entry. One explanation would be that EVgo has more resources in the area and can fix some malfunctioning chargers more quickly. However, none of these changes are significant, partially because the estimates for the effect of EVgo station entry on incumbent EVgo station health are very noisy.

The results of the difference in differences model shown in Table 2 show possible responses by incumbent EVgo and Electrify America stations. EVgo station quality improves following competitor entry, which could signify EVgo improving quality in response to competition. However, this result is not consistent across models (see Appendix Figure 8). The difference in differences model also shows a small decrease in station health at Electrify America stations following the entry of other Electrify America stations and competitors with the same



Notes: Data is for weekly station health score and spans October 2024 - December 2025.

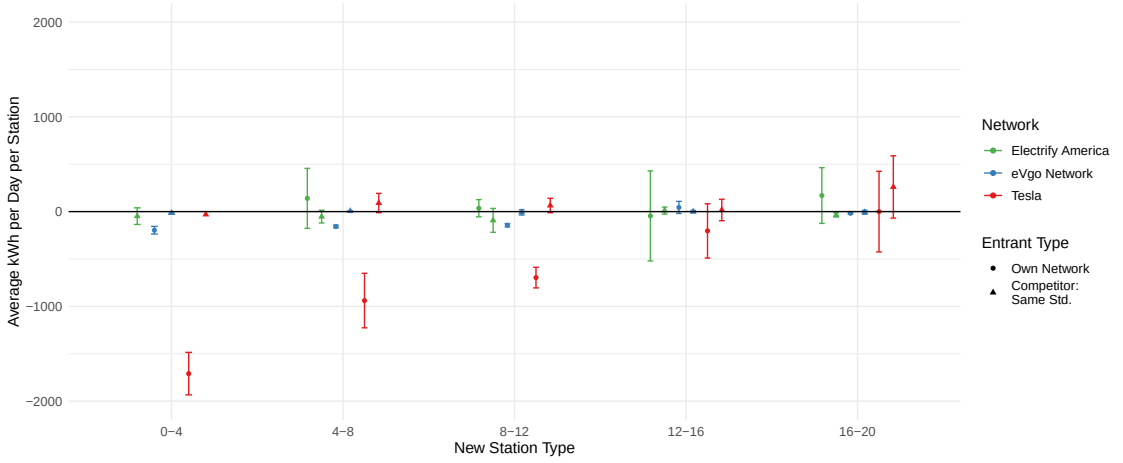
Figure 8: Event Study Estimates of Station Entry within Five Minutes on Incumbent Station Health

charging standard. The estimate for competitors is not robust to other specifications, but the estimate for the effect of own-network entry is. This likely captures that opening more chargers in an area decreases the incentive to keep incumbent chargers functioning since the stations are now less likely to hit capacity and the Electrify America app shows how many chargers are unused at any given time.

5.5 Effects by Distance

I explore whether the effect of station entry varies by distance. A standard Hotelings model would suggest that closer entrants have greater impacts. Indeed, Davis, McRae and Seira (2025) and Taylor and Muehlegger (2025) find that the effect of gasoline station entry on incumbent prices decreases as distance to the entrant increases, and that the effect size is much larger for the closest stations. To identify effects by distance, I group driving times into 4-minute driving times bands. I then estimate the difference in differences model interacting this driving time variable with the variables for number of stations or chargers.

I find that charging stations do respond greater to entry within a four minute drive than to entry at further distances. Figure 9 shows that the effect of own-network entry on incumbent charging volumes gradually decreases to zero as driving time rises to around 20 minutes for Tesla and 15 minutes for EVgo. Figure 10 that Tesla only lowers prices for incumbents within eight minutes of its own entrants. Electrify America decreases prices only for incumbents within four minutes of own-network entrants, and actually raises prices at incumbents further from entrants. This may reflect that the network chooses to place



Notes: Data is for total electricity consumption at each station and spans January 2022 - August 2024.

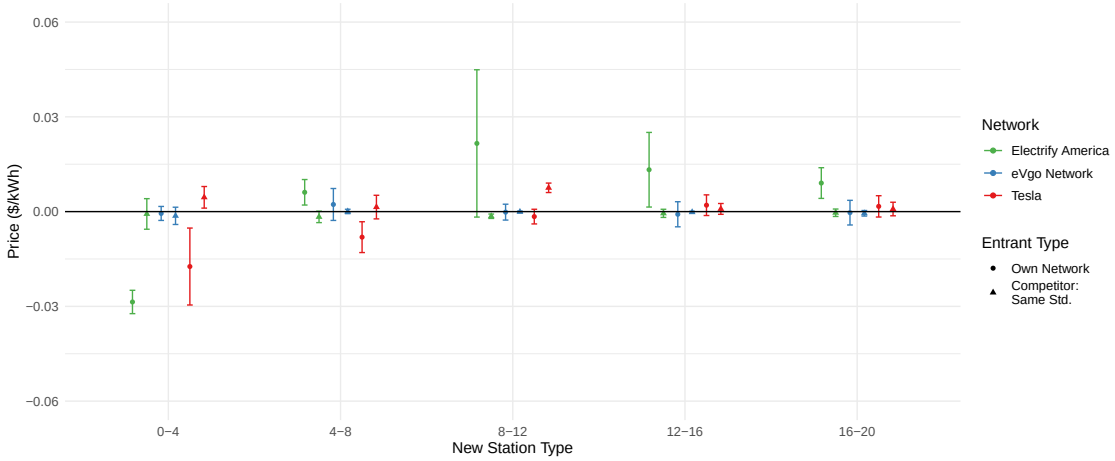
Figure 9: Estimates of Station Entry on Incumbent Charging Activity by Driving Time

entrants in higher demand markets and may be more likely to update prices at incumbent after opening new stations. Overall, my results mirror those in the literature, showing large effects for incumbents closest to entrants, which abate to zero as distance increases.

6 Conclusion

The EV fast charging market is a relatively new and growing market. However, while many microeconomic models would suggest an increasing number of competitors would drive down prices, prices have stayed high (relative to marginal cost) in this market so far. I show that this is because stations respond at most a small amount to additional competitors. Under my preferred specification, I find stations do not lower prices in response to competitor entry and can rule out price responses as large a share of margins as Davis, McRae and Seira (2025) and Taylor and Muehlegger (2025) find in retail gasoline markets. However, Tesla and Electrify America incumbent stations do respond to nearby own-network entry by lowering prices. This contrasts to the null or positive effects (depending on gasoline type) that Davis, McRae and Seira (2025) finds in retail gasoline, and is likely driven by capacity constraints the incumbent charging stations faced prior to own-network entry. Since networks are more likely to choose to open stations near existing stations facing capacity constraints, this result – while internally valid – does not provide information about what would happen if a social planner chose to open stations of the same type next to each existing station.

The demand response results may explain the mechanisms that lead to these price results. I estimate that quantities decrease at incumbents following own-network entry as the entrant



Notes: Data is for station-week-hour prices and spans October 2024 - December 2025.

Figure 10: Estimates of Station Entry on Incumbent Price by Driving Time

likely pulls some consumers away from the incumbent station. However, competitor entry has at most a relatively small effect on charging quantities – about two 20% to 80% car charges per day at non-Tesla stations and no effect at Tesla stations. This may suggest a high degree of market segmentation as drivers appear to only respond to new stations from the network whose stations they already use. In the extreme case of market segmentation, each network is a monopolist facing a constant marginal cost of electricity but also a capacity constraint.

There are a number of features of the EV fast charging market that could lead to strong brand preferences. One possibility is technological. Different charging standards mean that drivers without adapters can only charge at certain stations. However, both drivers and stations do not respond to the entry of competing stations regardless of the charging standard. Another possibility is that networks have managed to reduce the elasticity of demand through subscription plans. The major networks offer preferential rates for drivers who pay for monthly subscriptions to their networks.[13] Some cars also came with some amount of free charging at specific networks during the early 2020s, which would lead to inelastic demand while those benefits were available.

It is also possible that search costs lead to segmentation. Bernard et al. (2025) find relatively large price elasticities of demand, but focus on a setting with low search costs. They run their experiment on drivers that use a certain mobile app for payment and consider stations covered by that app. In my setting, there is no source of station locations and prices for all stations in my sample. If a driver wants to check prices at stations on different net-

[13] All new Teslas come with a free subscription for lower prices at Tesla's charging stations.

works, they will likely need to open multiple mobile applications. Tesla's vertical integration reinforces this issue. When a Tesla driver wants to refuel, the car's onboard system will show them the closest Tesla stations, but not other stations. If drivers check only certain applications, they will be unaware of prices at stations owned by competing networks, and may even not know those stations exist.

New stations increase driver welfare by reducing the time costs of refueling. However, because networks do not appear to compete on prices, consumers miss out on potential lower prices following entry. Segmentation is not an inherent feature of the fast charging market – regulation such as requiring price posting (either visibly at stations or through APIs that allow mobile apps to aggregate station prices) could boost consumer responsiveness and encourage price competition. Such regulation could enhance the benefits from station construction subsidies. The cost of such policy would be that it could reduce expected profits for potential stations, inhibiting future station construction. Future work studying the determinants of station entry could address the tradeoff between increased entry and lower prices.

References

Arcidiacono, Peter, Paul B. Ellickson, Carl F. Mela, and John D. Singleton. 2020. "The Competitive Effects of Entry: Evidence from Supercenter Expansion." *American Economic Journal: Applied Economics*, 12(3): 175–206.

Asensio, Omar Isaac, Elaine Buckberg, Cassandra Cole, Luke Heeney, Christopher R. Knittel, and James H. Stock. 2025. "Charging Uncertainty: Real-Time Charging Data and Electric Vehicle Adoption." National Bureau of Economic Research Working Paper.

Bernard, Louise, Andy Hackett, Robert D Metcalfe, Luca Panzone, and Andrew Schein. 2025. "The Impact of Dynamic Prices on Electric Vehicle Public Charging Demand: Evidence from a Nationwide Natural Field Experiment." National Bureau of Economic Research Working Paper 34600.

Bernardo, Valeria. 2018. "The effect of entry restrictions on price: evidence from the retail gasoline market." *Journal of Regulatory Economics*, 53(1): 75–99.

Busso, Matias, and Sebastian Galiani. 2019. "The Causal Effect of Competition on Prices and Quality: Evidence from a Field Experiment." *American Economic Journal: Applied Economics*, 11(1): 33–56.

Cole, Cassandra, Michael Droste, Christopher Knittel, Shanjun Li, and James H. Stock. 2023. "Policies for Electrifying the Light-Duty Vehicle Fleet in the United States." *AEA Papers and Proceedings*, 113: 316–22.

Colin Cameron, A., and Douglas L. Miller. 2015. "A Practitioner's Guide to Cluster-Robust Inference." *Journal of Human Resources*, 50(2): 317–372.

Davis, Lucas W., Shaun McRae, and Enrique Seira. 2025. "Competitive Effects of Entry in Gasoline Markets." *The Journal of Industrial Economics*, 73(4): 589–607.

Dorsey, Jackson, Ashley Langer, and Shaun McRae. 2024. "Fueling Alternatives: Gas Station Choice and the Implications for Electric Charging." National Bureau of Economic Research Working Paper.

Gamage, Tisura, Gil Tal, and Alan T. Jenn. 2023. "The costs and challenges of installing corridor DC Fast Chargers in California." *Case Studies on Transport Policy*, 11: 100969.

Garg, Teevrat, Ryan Hanna, Jeffrey Myers, Victor Tebbe, and David G. Victor. 2025. "Electric Vehicle Charging at the Workplace: Experimental Evidence on Incentives and Environmental Nudges." University of California San Diego Working Paper.

Joskow, Paul L. 1980. "The Effects of Competition and Regulation on Hospital Bed Supply and the Reservation Quality of the Hospital." *The Bell Journal of Economics*, 11(2): 421–447.

Li, Jing. 2023. "Compatibility and Investment in the U.S. Electric Vehicle Market." Working Paper.

Li, Shanjun, Lang Tong, Jianwei Xing, and Yiyi Zhou. 2017. "The Market for Electric Vehicles: Indirect Network Effects and Policy Design." *Journal of the Association of Environmental and Resource Economists*, 4(1): 89–133.

Remmy, Kevin. forthcoming. "Adjustable Product Attributes, Indirect Network Effects, And Subsidy Design: The Case of Electric Vehicles." *American Economic Journal: Economic Policy*.

Satterthwaite, Mark A. 1979. "Consumer Information, Equilibrium Industry Price, and the Number of Sellers." *The Bell Journal of Economics*, 10(2): 483–502.

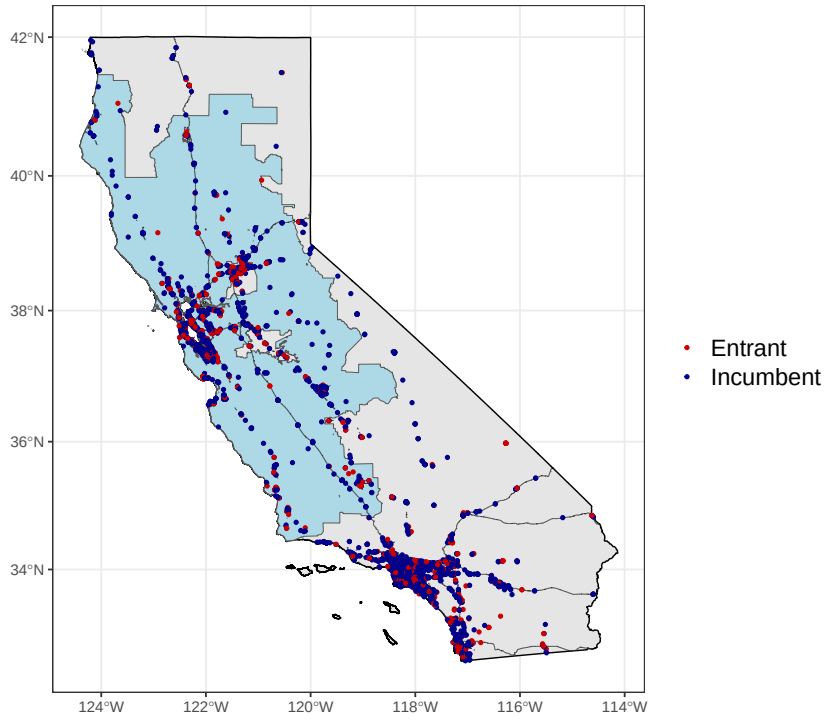
Sommer, Stephan, and Colin Vance. 2021. "Do more chargers mean more electric cars?" RWI - Leibniz-Institut für Wirtschaftsforschung, Ruhr-University Bochum, TU Dortmund University, University of Duisburg-Essen Ruhr Economic Papers 893.

Springel, Katalin. 2021. "Network Externality and Subsidy Structure in Two-Sided Markets: Evidence from Electric Vehicle Incentives." *American Economic Journal: Economic Policy*, 13(4): 393–432.

Taylor, Reid, and Erich Muehlegger. 2025. "The Effects of Competition in the Retail Gasoline Industry." Federal Reserve Bank of Dallas Working Paper 2509.

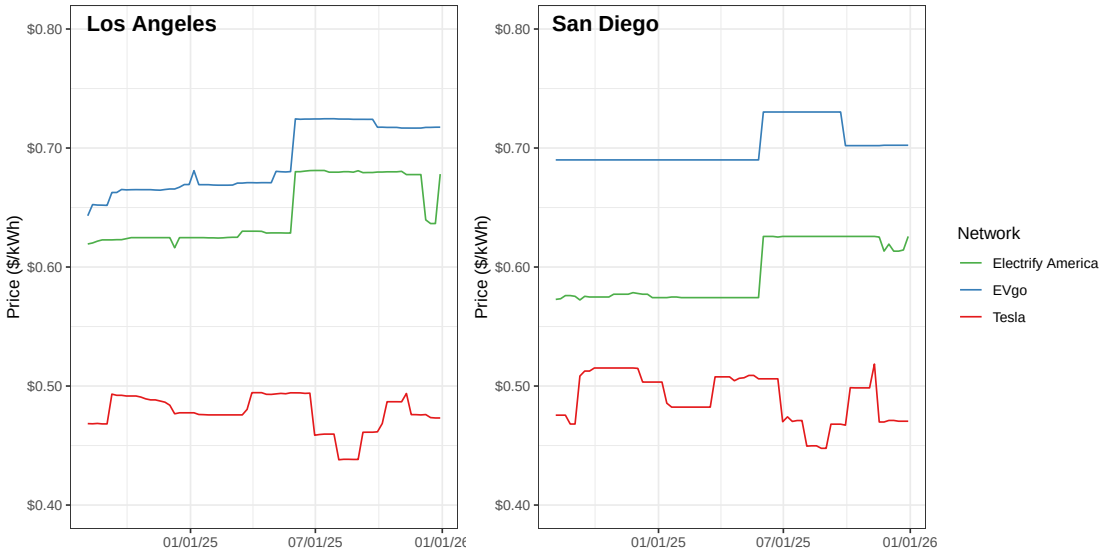
USDOT. 2023. "Charger Types and Speeds."

Zhou, Yiyi, and Shanjun Li. 2018. "Technology Adoption and Critical Mass: The Case of the U.S. Electric Vehicle Market." *The Journal of Industrial Economics*, 66(2): 423–480.

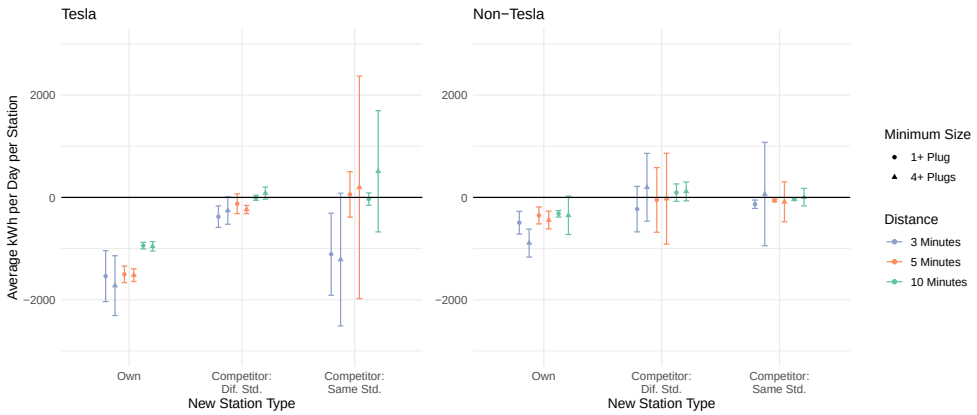


Notes: Blue-shaded area represents PG&E territory.

Appendix Figure 1: Map of Incumbent and Entrant Station Locations

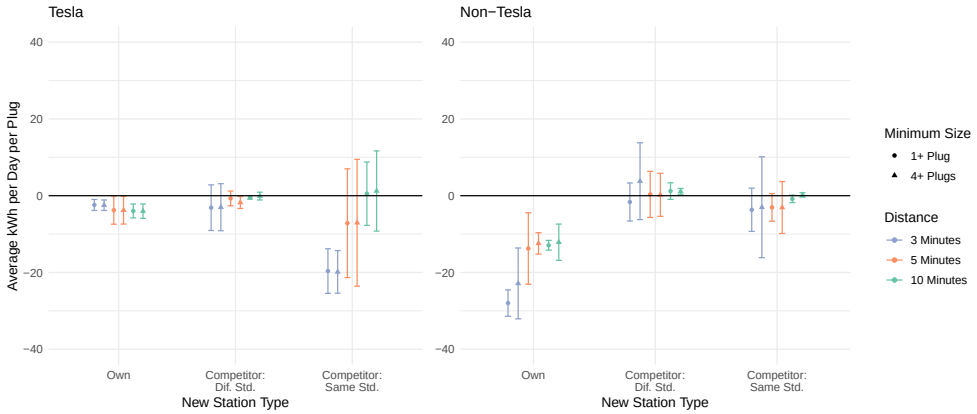


Appendix Figure 2: Average Weekly 5 PM Prices across Networks



Notes: Data is for total electricity consumption at each station and spans January 2022 - August 2024.

Appendix Figure 3: Difference in Difference Estimates of Station Entry on Incumbent Charging Activity

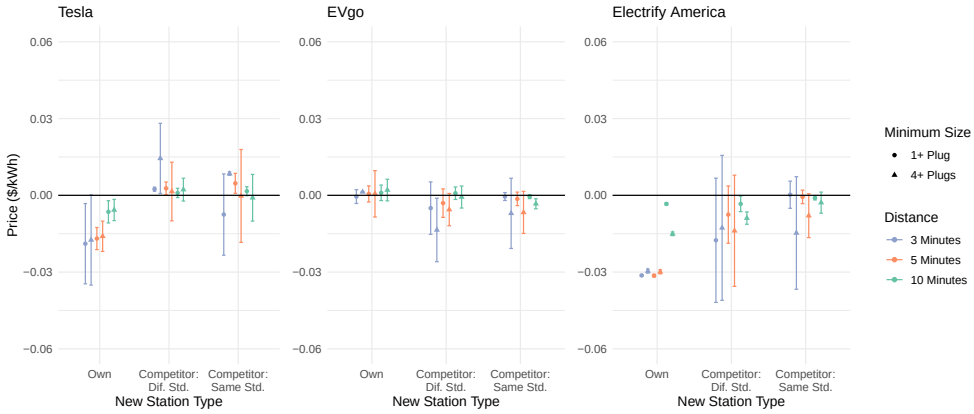


Notes: Data is for total electricity consumption at each station and spans January 2022 - August 2024.

Appendix Figure 4: Difference in Difference Estimates of Charger Entry on Incumbent Charging Activity

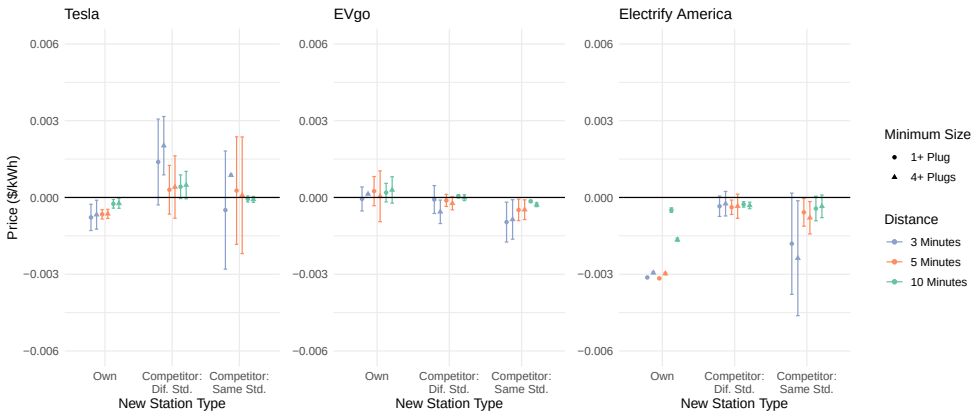
Appendix Table 1: Entrant Characteristics

	Tesla	EVgo	Electrify America	Other
Nearby (Total) Incumbent Characteristics				
Own stations	0.2	0.4	0.1	0.2
Competing stations, different standard	1.0	0.3	0.8	0.2
Competing stations, same standard	0.0	0.7	0.7	1.3
Own chargers	3.0	1.3	0.5	0.4
Competing chargers, different standard	3.4	4.4	16.4	2.6
Competing chargers, same standard	0.0	3.1	1.5	5.7
Entrant Characteristics				
Chargers	13.1	6.0	5.7	3.9
First four weeks kWh/day	4312	607	429	219
First four weeks kWh/charger/day	333	97	83	65



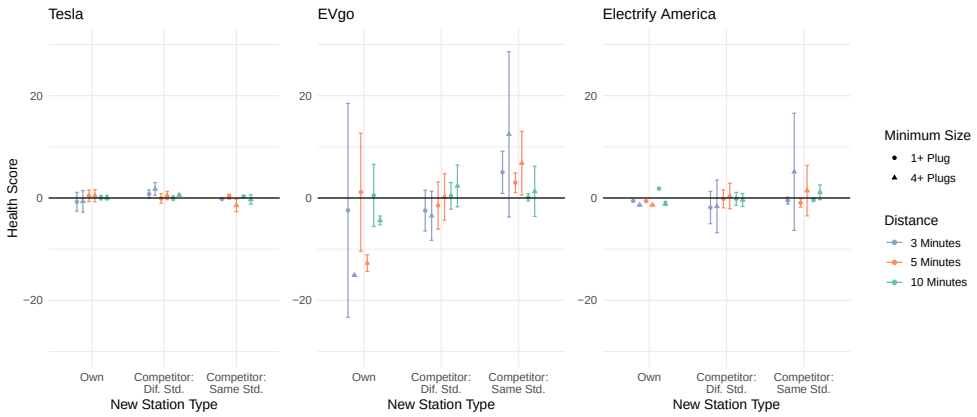
Notes: Data is for station-week-hour prices and spans October 2024 - December 2025.

Appendix Figure 5: Difference in Difference Estimates of Station Entry on Incumbent Price



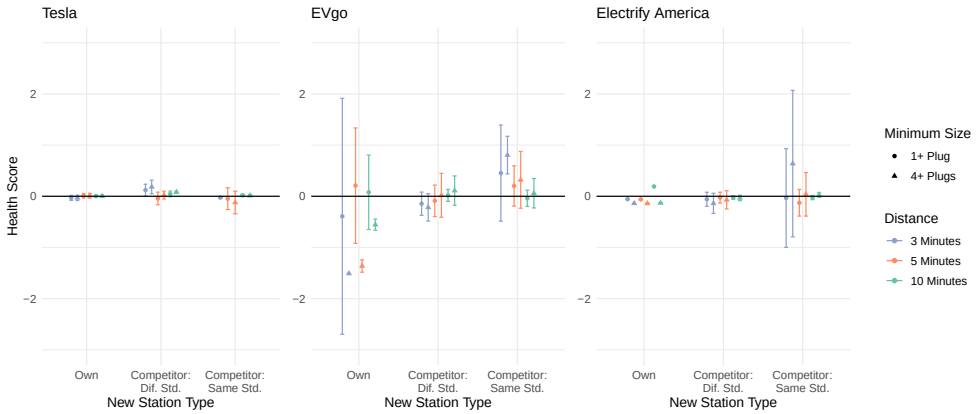
Notes: Data is for station-week-hour prices and spans October 2024 - December 2025.

Appendix Figure 6: Difference in Difference Estimates of Charger Entry on Incumbent Price



Notes: Data is for weekly station health score and spans October 2024 - December 2025.

Appendix Figure 7: Difference in Difference Estimates of Station Entry on Incumbent Station Health



Notes: Data is for weekly station health score and spans October 2024 - December 2025.

Appendix Figure 8: Difference in Difference Estimates of Charger Entry on Incumbent Station Health