What's Driving High Electric Vehicle Fast Charging Prices?

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Abstract

Electric vehicle fast charging is more costly than home charging, which could slow electric vehicle adoption and place higher costs on low-income households. Using novel data on station-level quantities, prices, and marginal costs, I combine reduced-form and structural methods to identify price-setting conduct across charging networks. I employ a difference-in-differences approach to show that, contrary to standard theory, stations do not lower prices in response to nearby competitor entry. I build a model of heterogeneous consumer demand for fast charging and use the structurally-estimated parameters to calculate the social surplus maximizing prices. I show that charging prices include a markup above what is necessary to recover fixed costs, and estimate that lowering prices to social surplus maximizing prices could increase social surplus by 8-10% while still recovering fixed costs. Social surplus maximizing prices remain above marginal operating costs due to capacity constraints, which require stations to raise prices to clear the market. My results suggest that increasing competition can reduce markups by up to half, but that policy would need to address charging supply or inelastic consumer demand to further reduce markups.

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1 Introduction

Many of the world's largest car markets have set ambitious goals for electric vehicle (EV) adoption.[1] A hurdle in meeting these goals will be making EVs appealing for drivers who cannot charge at home, a population that has been resistant to purchasing EVs. Many governments have focused on public fast chargers as the solution to this challenge. California, which is home to one-third of United States EVs and the focus of this paper, estimated in 2024 that it would need 83,000 fast chargers to support a fully electric car fleet – a notable increase from the 10,000 it had in 2023 – and has earmarked around $350 million for fast charger subsidies since 2024 (Davis et al., 2024). Fast chargers can refuel an EV in 20-60 minutes (compared to 4-50 hours at other chargers), reducing the time cost of owning an EV for drivers without access to a charger at home or work.

The premium speed comes at a premium price. Fast charging is on average three times as expensive as home charging in the United States (Paris, 2025). High charging prices have the potential to create inefficiency and inequity. Prices above the social marginal cost could lead to deadweight loss from inefficiently low EV adoption and use by drivers without access to chargers at their home or workplace. The ability to charge at home is largely determined by whether a household has its own garage, which is strongly correlated with income. Fast charging prices remaining high could result in inequitable fueling costs.

In this paper, I explore the causes of high prices and estimate the impacts on social surplus. One barrier to research on pricing in this market is that charging networks typically share prices only through their own mobile applications, leading to an absence of centralized pricing data. I construct a novel weekly panel of hourly prices at the three largest networks in California – Tesla, EVgo, and Electrify America – by manually collecting data from networks' mobile applications. The panel includes 19 months of week by hour price data for 58% of all charging stations in California. I build a second panel of EV charging volumes and marginal operating costs in Northern California using four years of electricity consumption and rate data from Pacific Gas & Electric Company, one of the largest utilities in the United States. Combining the two datasets, I show that, on average, fast charging prices are more than double marginal operating costs, reflecting markups an order of magnitude greater than those in the retail gasoline industry.

Standard models predict that product differentiation, strong consumer preferences, and fixed costs can sustain markups even in the long run. I provide an additional theoretical mechanism: capacity constraints result in higher market-clearing prices. When station

[1] Although the United States has not set any targets, a number of states have their own and thirteen formed the Affordable Clean Cars Coalition to help meet their targets.

capacity binds in the short run, the constrained marginal cost curve becomes vertical at capacity, so prices must exceed marginal operating costs to clear the market. I decompose the effects of differentiation, consumer preferences, fixed costs, and capacity constraints on observed markups to assess the relative contribution of each mechanism.

I start by focusing on the effects of station openings using a difference-in-differences event study approach. I match stations within five minutes of an entrant to stations that are part of the same charging network, exposed to the same market trends, and more than ten minutes from any entrant. Contrary to results from other markets, I find that charging volumes and prices at existing stations remain unchanged following competitor entry. However, entry does decrease charging volumes by 14% at nearby stations in the same network, suggesting that consumers are willing to substitute within but not across networks. Stations do not compete on prices, and have no incentive to do so because consumers do not substitute across networks. These results indicate that subsidizing entry and increasing the number of competitors in the market is unlikely to decrease prices.

I then assess the consumer preferences, market clearing, and fixed costs explanations for markups. I build and estimate a model of heterogeneous consumer demand for fast charging and find very low cross-station and cross-hour price elasticities, suggesting strong consumer preferences. I use the structurally-estimated demand parameters and observed costs to solve for social surplus and profit maximizing prices in this setting. The results show that all three networks set prices near the linear prices that maximize profit in the fast charging market.

I show that high prices are not fully explained by capacity constraints or fixed costs. I calculate that equating quantity demanded and supplied to maximize social surplus requires 48% markups above marginal operating costs, indicating that the market-clearing condition explains slightly less than half of observed markups. Incorporating fixed cost recovery explains more, but not all, of markups. My results suggest that if observed prices decrease to the linear prices that most efficiently recover fixed costs, social surplus would increase by 8-10%, though reduced profits could deter station entry.

Overall, I find that markups are high in the fast charging market and charging networks do not compete on prices. I show that strong consumer preferences and product differentiation are the best explanations for the lack of competition and high markups. However, half of the average observed markup is efficient in the short run given capacity constraints and rigid consumer preferences. My results suggest that increasing competition can reduce markups by up to half, but that policy would need to address charging supply or inelastic consumer demand to further reduce markups.

I contribute to three literatures. First, I contribute to the literature on EV charging. A number of papers have estimated the effect of charger supply on EV purchases (Cole et al.,

2023; Springel, 2021; Sommer and Vance, 2021; Zhou and Li, 2018; Li et al., 2017; Remmy, forthcoming). I provide the first estimates of charger supply on prices and charging behavior. Importantly, I show that consumers exhibit strong network preferences that are not explained by charging standard differences. This is particularly relevant for work showing potentially large benefits of standardizing plug types, which assumes potential drivers choose cars based on existing stations' charging standard rather than network (Li, 2023). My findings suggest that *current* EV drivers may not benefit from standardization given their strong network preferences. I also provide the first model-based estimates of demand elasticities for fast charging stations in the United States. This adds to randomized control trial evidence from Bernard et al. (2025) on elasticities of demand for public charging in the United Kingdom and Bailey et al. (2025) and Garg et al. (2026) on how drivers respond to price incentives for home and workplace charging, respectively.

Second, I contribute to the literature on market entry and competition by showing no consumer or firm response to competitor entry. My results contrast with the retail gasoline literature, where Taylor and Muehlegger (2025) and Davis, McRae and Seira (2025) document price decreases at incumbent stations. The lack of price response in the fast charging market is rationalized by the finding that station entry does not impact charging volumes at nearby competitors. My finding that consumers substitute within but not across networks suggests that consumer preferences or demand-side frictions, rather than the supply-side frictions Arcidiacono et al. (2020) find at grocery stores, may explain the lack of price response in the fast charging market.

Third, I contribute to the literature on fixed-cost recovery by comparing the efficiency of linear prices and two-part tariffs in the presence of capacity constraints. "Ramsey prices" are the set of linear prices that minimize deadweight loss while recovering fixed costs (Boiteux, 1956; Ramsey, 1927). Though Ramsey prices are the most efficient set of linear prices, they still lead to deadweight loss, and are a second-best option to two-part tariffs (Feldstein, 1972; Littlechild, 1975). I modify the standard Ramsey problem to account for short-run capacity constraints and show that Ramsey prices can result in minimal deadweight loss and be nearly as efficient as two-part tariffs when capacity constraints bind.

The paper proceeds as follows. Section 2 provides information on California's fast charging market, the setting for this paper. In Section 3, I describe the data collection process and provide descriptive statistics on the fast charging market. Section 4 provides theoretical explanation for markups. In Section 5, I present estimates of the impact of station entry on charging quantities, price, and quality. I build and estimate a model of heterogeneous consumer demand in Section 6. In Section 7, I use the parameters from the demand model to calculate profit and social surplus maximizing prices. Section 8 concludes.

2 Fast Charging

Electric vehicle charging is generally classified into three levels based on speed. Level 1 and level 2 charging take 40-50 and 4-10 hours to charge a vehicle, respectively. In this paper, I focus on level 3 charging, often called DC fast charging or simply fast charging, which can refuel a car in 20-60 minutes.[2] Many governments have opted to subsidize fast charging stations to enable longer trips and facilitate refueling for those who cannot charge at home or work.

The downside to fast charging is the cost. Chargers are expensive and often require upgrades to electricity grid infrastructure before they can be connected. Stations generally cost $40,000 to $400,000 per charger depending on the speed of the charger, expense of upgrading local grid infrastructure, and number of chargers at the station (Gamage, Tal and Jenn, 2023; Li, 2023; Miyatra, 2025). An additional barrier to installation is the time it takes to upgrade the grid before chargers can be connected, which can take several months (Gamage, Tal and Jenn, 2023).

2.1 The Fast Charging Market

The fast charging market in California is highly concentrated. Stations are owned by centrally-organized charging networks that operate statewide.[3] Three networks, Tesla, EVgo, and Electrify America, operate 64% of stations.[4] Tesla, the largest of the three, builds larger stations than nearly all other networks; it operates 30% of stations and 57% of fast chargers in the state. Networks have raised consumer search costs through only listing prices on their own mobile applications. Tesla and Electrify America all share charger availability data with Google Maps, but none of the three shares prices.[5]

Another key way that stations have segmented the market is through differences in charging standards. 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 for NACS plugs and instead were equipped for either CCS (also called J1772 combo) or CHAdeMO plugs. Further, other stations did not offer NACS charging until 2025, but have begun to incorporate NACS plugs in new stations and retrofit some existing stations with

[2] I provide a table with more information on the three charging levels in Table A.1.

[3] There are exceptions to this, but most stations are operated by networks and not franchisees. This is a notable difference from the retail gasoline market.

[4] I define stations as any set of multiple chargers operated by a network in a single location.

[5] Another source of charging station information is PlugShare, a web and mobile application that aggregates EV charger information. Neither Tesla nor Electrify America shares prices on PlugShare.

[6] Li (2023) provides a good history of charging standard development.

NACS plugs. Automakers sell adapters to allow owners to charge at stations with different charging standards, but development of NACS adapters has been slow and they did not become readily available until the second half of 2025. As a result, charging standard differences may still play a key role in product differentiation.

Subscription plans may further sement the market. Tesla, EVgo, and Electrify America offer subscription plans that lower volumetric prices (by 15-40%) in return for a monthly fee. Tesla provides a free lifetime subscription for new car buyers. In this paper, I use the default prices from each network (or clarify which set of prices I am referencing). For Electrify America and EVgo, these are the prices that drivers without a paid monthly subscription pay. For Tesla, this can be viewed either as the prices for a Tesla driver or for a non-Tesla driver who purchases a monthly subscription. More than half of EVs registered in California are Teslas, so one can interpret the default price as the price the median or modal driver in California faces.

3 Data

3.1 Station Characteristics

I collect a list of public fast charging stations and characteristics for those stations from the Alternative Fueling Station Location API run by the Department of Energy's Alternative Fuels Data Center (AFDC). The data include station address, geographic location, number of fast chargers, and charging standards (NACS, CCS, and CHAdeMO) available at public charging stations. I use this station list as the foundation for building weekly panels of station prices, charging volumes, and quality.

3.2 Price Data

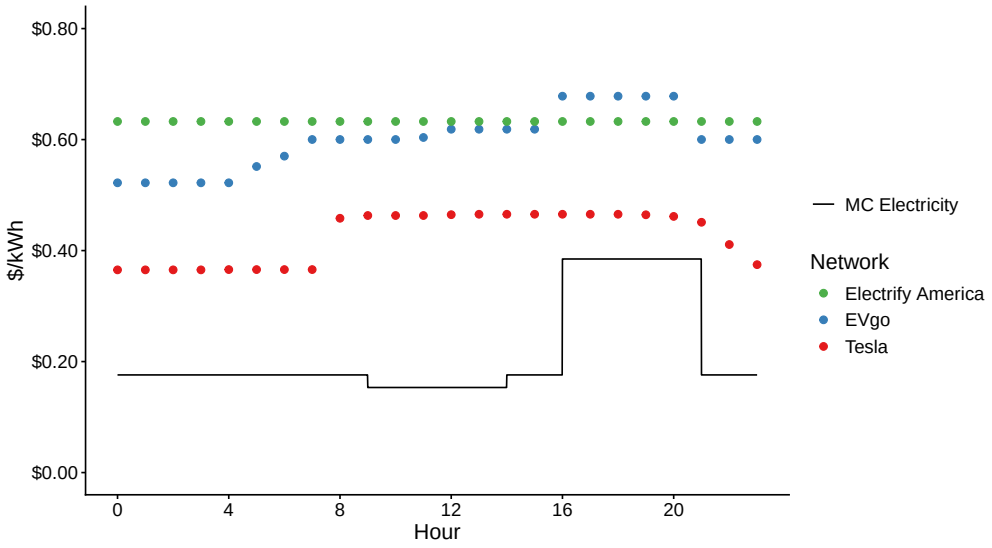
Each week from October 2024 through May 2026, a team of research assistants and I collected hourly volumetric prices[7] for all Tesla, EVgo, and Electrify America DCFC stations in California. Data comes from each company's mobile application and PlugShare, a third party aggregator of charging station data, which posts EVgo prices. The list of stations for a week comes from querying the Alternative Fueling Station Location API for a station list each Saturday. We collected prices for Tesla, EVgo, and Electrify America stations on the station list between Saturday and the following Friday [8] My recorded weekly prices at a

[7] I do not include each network's fees for idling at the station after charging or Tesla's congestion fee for charging above 80%.

[8] I provide a more detailed explanation of the process in Appendix B.1.

station will not capture price changes that occured during that week if the changes occurred after data was collected.

We collected hourly prices to account for time-of-use pricing. Figure 1 shows networks' average hourly prices at DCFC stations served by PG&E during October 2025. The black line on the figure represents the marginal cost of one kWh of electricity for stations on the most commonly used electricity tariffs during this period (discussed further in Section 3.3).[9] The figure shows that markups above marginal operating costs are high in the fast charging market and vary throughout the day. The quantity-weighted average markup above marginal operating cost from October 2024 to October 2025 was 109%, which is an order of magnitude greater than average markups in the retail gasoline industry.[10]



Notes: Data are for October 2025. Prices are averaged across all stations operated by each network in PG&E's service area. "MC Electricity" is the per kWh electricity cost under the electricity rates most frequently used by fast charging stations.

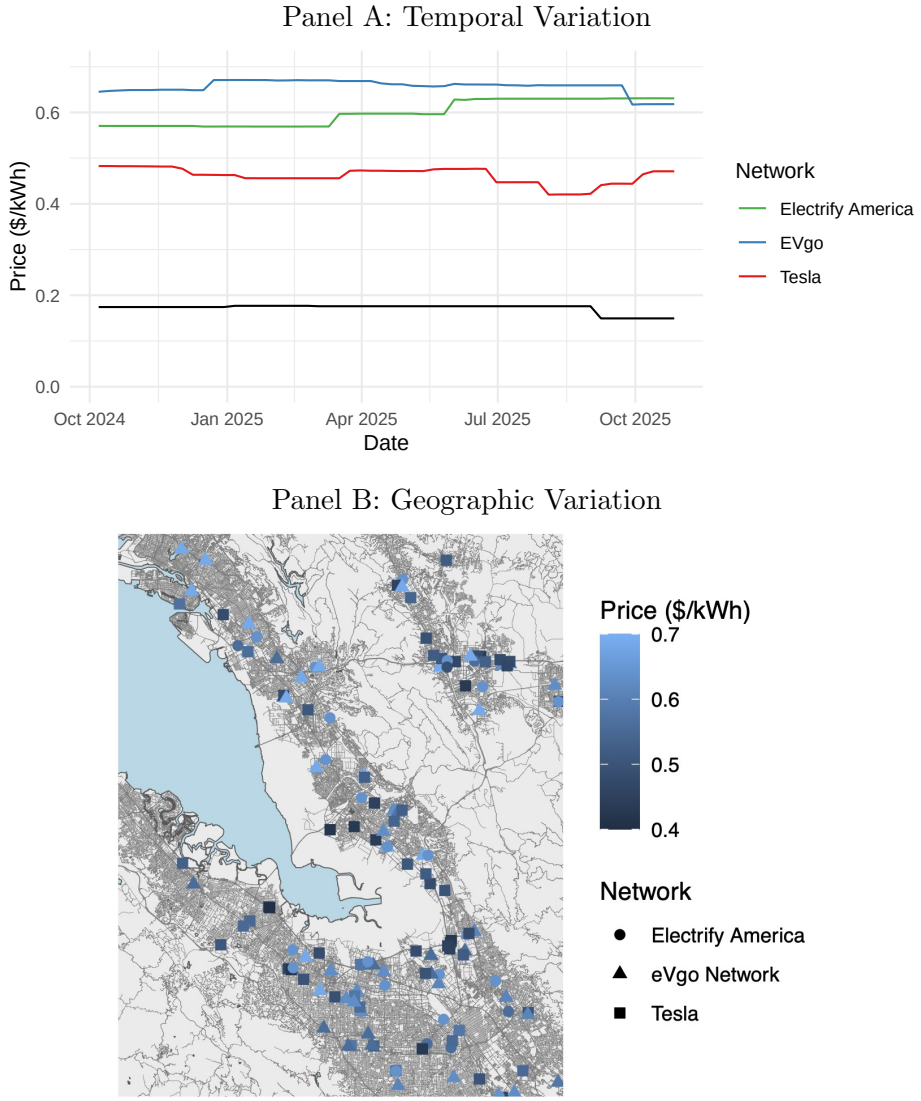
Figure 1: Average Hourly Prices and Marginal Costs at DCFC Stations in PG&E Service Area

In total, the data include 2.6 million station-week-hour prices across 1,407 out of the 1,414 charging stations operated by Tesla, EVgo, and Electrify America on the AFDC's list. Figure 2 shows price variation over time and across geography. Networks change their schedule of hourly prices rarely, so most price variation comes from within-day and across-station price variation. Networks do not change price schedules during the same week or in

[9]Smaller stations were more likely to use the lower capacity tariffs, which charged slightly higher prices per kWh that were within $0.02/kWh of the black line at all hours.

[10]Providing charging does not require inputs beyond electricity, so I consider the marginal operating cost to be the cost of purchasing one kWh. There are other fixed operating and maintenance costs such as maintenance and monthly demand charges that I defer to Section 7.

the same direction, which is suggestive that pricing is not collusive. There is spatial variation in prices across a network's stations. Tesla and EVgo predominantly used time-of-use pricing (where prices vary throughout the day) for most of the sample period while Electrify America used a single price at most stations. In November of 2025, Tesla moved to demand-based pricing at most of its stations. These stations switched from prescheduled time-of-use prices to a high, medium, or low price based on the amount of current use at the station. I cannot view hourly prices at these stations and drop all station-weeks using demand-based pricing from analysis and limit my demand estimation to the period preceding this change.



Notes: Both panels show 2 PM charging prices for stations served by PG&E. Panel A presents average weekly price by network. Panel B shows average price at each of a subset of stations during October 2025.

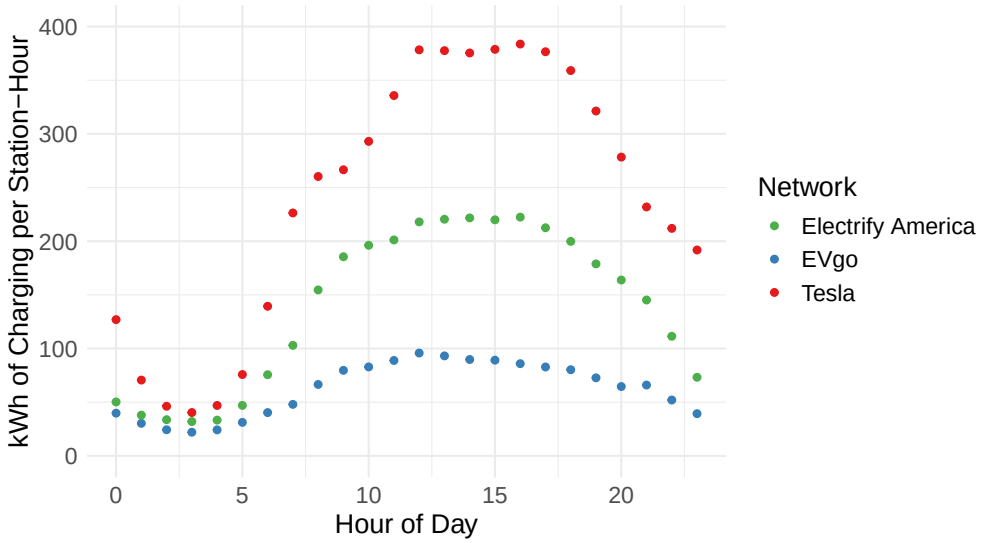
Figure 2: Variation in 2 PM Charging Prices

3.3 Electricity Utilization and Billing Data

I obtain station-level electricity consumption and billing data from Pacific Gas & Electric Company (PG&E), the largest electric utility in California and one of the largest in the United States. The data include both meter-level electricity consumption measured in kWh and rate payer category from 2022 through 2025. The sample includes fast charging stations that PG&E identified in their data or matched to addresses from the AFDC station list.

I convert the raw electricity usage data into an approximation of the amount of electricity used for charging each hour. The raw meter data incorporates all metered electricity consumption at the location, which includes electricity for payment systems and lights. I attempt to remove non-charging electricity consumption by subtracting the lowest observed electricity use for each station. I classify the remainder as electricity used for charging.[11]

I plot the average hourly use per station by network in Figure 3. Tesla has larger stations than Electrify America and EVgo (see Table 1), and Tesla and Electrify America chargers generally have higher charging speeds. I plot use per charger in Figure A.1, which switches the rank order of Tesla and Electrify America. It is also clear that charging activity increases throughout the morning, peaks in the afternoon, and decreases in the evening. This is notably different from grid-wide electricity use which peaks in the evening as individuals return from work and use appliances.



Notes: Data are for October 2025. Electricity utilization is averaged across all stations operated by each network that are served by PG&E.

Figure 3: Average Hourly Electricity Use at DCFC Stations served by PG&E

[11] I document this process more thoroughly in Appendix B.2.

Using the rate payer category and historical rates, I can determine the marginal cost of one kWh for each station at each hour of the day. Combining the use and rate payer category data, I can measure hourly charging quantities and marginal operating costs at 455 stations that I can identify in the PG&E data and do not share a meter with another station.

In Table 1, I combine the PG&E, price, and station data to provide summary statistics by network. Tesla stations are larger than EVgo and Electrify America stations and sell more kWh of charging. The price data covers almost the entire population of Tesla, EVgo, and Electrify America stations in the state. I have electricity use data for a smaller sample of stations, which matches the broader population of stations for those networks in terms of station size, market congestion, and average price.

Table 1: Summary Statistics

	Tesla	EVgo	Electrify America	Other
All California				
Stations	663	454	297	1014
Plugs per Station	16.4	4.9	4.9	5.2
Stations within 5 min.	2.4	2.7	2.1	2.6
Price Data				
Stations	657	454	296	0
Plugs per Station	16.4	4.9	4.9	
Stations within 5 min.	2.4	2.7	2.1	
Price	$0.43	$0.59	$0.61	
Electricity Use Data				
Stations	178	125	90	62
Plugs per Station	15.1	5.5	4.5	6.0
Stations within 5 min.	2.1	3.0	1.9	2.9
Price	$0.44	$0.58	$0.61	
Daily kWh	5761.0	1276.5	2478.7	1060.2

3.4 Station Quality Data

My last data source is a measure of quality from Paren, a company that collects charging station data. I use Paren's Station Health Score, which is a weekly index of station quality. The score is calculated using a proprietary algorithm that incorporates a charger's uptime and share of charging session 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 a 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 and the majority of

Tesla stations in 2025.[12] As part of my data use agreement, I do not present quality results disaggregated by network.

Paren began collecting price data in 2025. I match my station-week-hour price data with their price data for September 2025 to assess the accuracy of my data. I find that more than 99% of station week-hour prices match across the two datasets, providing support for the accuracy of my price data.

4 Conceptual Framework

Markups are an inherent feature of industries with fixed costs and product differentiation. In Bertrand competition, product differentiation allows firms to have price setting power (Tirole, 1988). I simplify the model of monopolistic competition from Perloff and Salop (1985) to provide a stylized model that illustrates how various other features of the charging market contribute to markups. I develop a more complex model of consumer behavior in Section 6, but the simple setup of this model makes it ideal for exposition.

Consider a consumer that must choose where to charge among n stations indexed by i. The consumer's preference for charging at each station is given by the vector $\boldsymbol{\theta} = (\theta_1, ..., \theta_n)$ where θ_i includes preferences over nearby amenities (such as grocery stores, restaurants, etc.), charging network, charging standard, and travel costs. The vector of prices at each station is $\boldsymbol{p} = (p_1, ..., p_n)$. The consumer chooses to charge at the station that maximizes net surplus $s_i = \theta_i - p_i$ for $i \in 1, ...n$.[13]

For simplicity, let all consumers' preferences for stations be independent and identically distributed $\theta_i \sim U[-1, 1]$. The cumulative distribution function is $G(\theta_i) = \frac{\theta_i + 1}{2}$. The probability that a consumer prefers station i to station j is

$$\Pr(s_i \geq s_j) = \Pr(\theta_j \leq \theta_i + p_j - p_i) = G(\theta_i + p_j - p_i) = \frac{\theta_i + p_j - p_i + 1}{2}. \tag{1}$$

4.1 Profit Maximizing Prices

Aggregating across all L consumers and n stations in the market yields station quantities for a given vector of prices, $Q_i(\boldsymbol{p})$. I calculate the Nash-Bertrand equilibrium price:

[12] Paren initially had limited coverage of Tesla stations, but expanded their Tesla station data in 2025.

[13] For simplicity, I have omitted the outside option which would set an additional restriction that $s_i \geq \bar{v}$ for the consumer to choose station i. In Section 6, I incorporate the outside option.

$$p(n) = c + \frac{L/n}{L/2} = c + \frac{2}{n} \tag{2}$$

where price equals marginal cost c plus a markup inversely proportional to the number of firms in the market, n. I provide a proof that $p(n)$ maximizes profit in Appendix C.1.

The model has three key implications for the fast charging market. First, station entry increases competition and reduces prices and markups. As n increases, the markup term $\frac{2}{n}$ decreases and p decreases.[14] Second, product differentiation sustains markups at equilibrium. Third, preference strength and product differentiation impact equilibrium markups. To see this, let $\theta_i = \beta\theta_0$ where β is a measure of preference strength and now $\theta_0 \sim U[-1, 1]$. Then $p(n) = c + \frac{2\beta}{n}$ and the markup is proportional to preference strength. As preferences for charging networks or station amenities increase, equilibrium markups also increase. Greater product differentiation increases relative preference strength and leads to greater markups.

4.1.1 Capacity Constraints

The stylized model does not account for the time-varying demand and marginal costs shown in Figure 3 and Figure 1, respectively. In the charging market, networks set station-hour-specific prices and customers choose where and when to charge. If all chargers at a station are full, customers are unable to charge there.

In the short run, networks cannot increase their supply; building new stations or expanding existing stations takes months. At a station's maximum capacity, the marginal cost becomes vertical. In Figure 5, I illustrate the simple case where a station faces different demand in two periods and can sell no more than $\bar{Q}$ units of charging in each period. In both periods, the profit maximizing price is determined by the intersection of the marginal revenue and marginal cost curves. The profit maximizing price during the off-peak period, $P^{\pi}_{\text{O-P}}$, comes from the standard MR=MC result and includes a markup over marginal cost.

The figure illustrates the case where peak-period marginal revenue intersects marginal cost on the vertical portion of the marginal cost curve.[15] This intersection occurs at a lower quantity than the intersection of peak-period marginal revenue and marginal operating cost, $\text{MC}_{\text{Oper.}}$. Therefore, the capacity constraint binds during the peak period and the profit

[14] This implication is reliant on the uniform distribution of θ, which I use to make the relationship between variables more clear. More generally, in many models, including the standard mixed Logit I use in Section 6, an increase in the number of firms leads to lower prices (Anderson and de Palma, 1992).

[15] It is also possible for demand to intersect marginal cost on the vertical portion and marginal revenue to intersect marginal cost on the horizontal portion. This case is the same as the off-peak demand case. The station would price based on the quantity at which marginal revenue equals marginal cost, which is less than the quantity at which demand and marginal cost intersect.

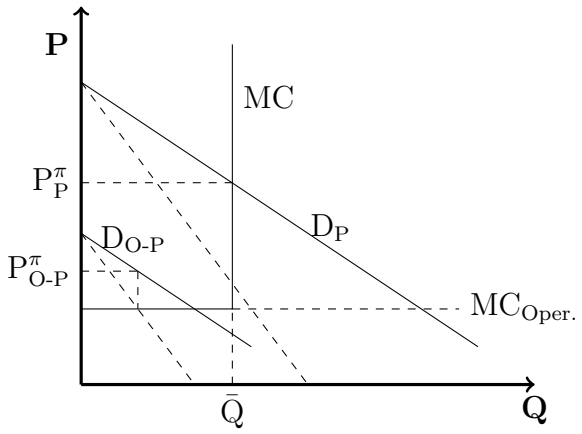


Figure 4: Short-Run Profit Maximizing Prices with Capacity Constraints

maximizing price, P^{π}_{P}, is higher than it would be without the constraint. $P^{\pi}_{P} = MC$ and is efficient, but is also greater than $MC_{Oper.}$, so the station earns positive profits.

4.1.2 Long-Run Markups

In the long run, networks choose to build more stations as long as the expected marginal surplus from each station exceeds fixed cost K. In the stylized model stations choose to enter until $p(n) = \frac{nK}{L} + c$. Therefore, markups persist even in the long-run equilibrium if marginal costs are non-increasing and $K > 0$.

4.2 Efficient Pricing

4.2.1 Capacity Constraints

In order to understand the magnitude of markups, it is helpful to establish a benchmark. For the remainder of this paper, I will classify markups as markups above *marginal operating cost* because this is the margin that reflects how "high" fast charging prices are. As shown in Figure 4, a benevolent social planner may set prices that include markups above marginal operating costs, so comparing markups to zero would overestimate the amount of deadweight loss from markups. In Figure 5, I return to the two-period example from Figure 4, now from the perspective of the social planner. Short run efficient prices are those at the intersection of the demand and marginal cost curves.[16]

[16] I have dropped external costs and moved from social marginal cost to private marginal cost. Borenstein and Bushnell (2022) focus on the importance of considering external costs in determining efficient electricity rates. They show that electricity rates in California are well above social marginal cost, which means the private cost that charging stations face is greater than the social marginal cost of producing that electricity. Therefore, $P^{*}_{O\text{-}P}$ does not maximize social surplus, but rather maximizes surplus contingent on the restriction that the charging network not take losses on each unit of charging. Truly maximizing social surplus would

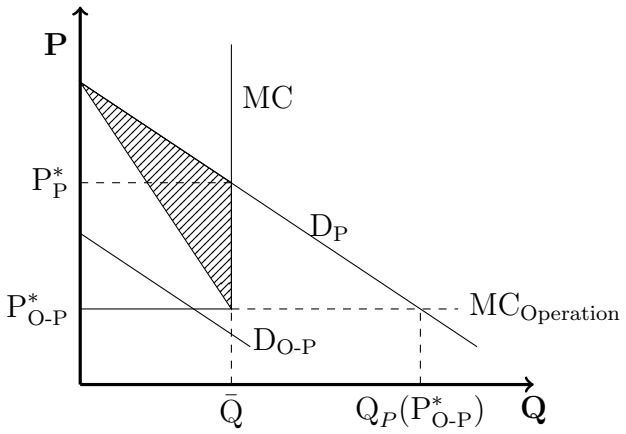


Figure 5: Short-Run Efficient Prices with Capacity Constraints

During the peak-period, the social surplus maximizing price P^*_P is equal to the profit maximizing price P^π_P shown in Figure 4. Charging the lower price of $P_P = P^*_{O\text{-}P}$ would lead to excess demand, and there is no guarantee that charging will be allocated to the consumers who receive the greatest benefit. To clarify this point, suppose that charging is randomly allocated across all consumers willing to pay $P_P = P^*_{O\text{-}P}$ during the peak-demand period. The expected willingness to pay of any consumer who receives charging is halfway between D_P's P-intercept and $P^*_{O\text{-}P}$. The shaded region represents the expected deadweight loss from this random allocation, which does not increase quantity and leads to a lower average willingness to pay (relative to the market-clearing price, P^*_P) among consumers who are able to charge.

This example shows that profit maximizing markups can be efficient. When demand is sufficiently high, the social planner and profit maximizing firm choose the same price. P^*_P equates quantity supplied and demanded to clear the market. It is the lowest price that eliminates the deadweight loss from misallocation, and the highest price that eliminates deadweight loss from an inefficiently low charging quantity.

4.2.2 Long-Run Prices

In the long run, capacity constraints still bind if $K > 0$. The social planner chooses to add capacity if the additional social surplus from increased peak-period utilization exceeds the fixed costs. K determines the efficient wedge between P^*_P and $P^*_{O\text{-}P}$ in Figure 5.

require either PG&E to lower the per-unit cost of electricity or for the state to pay per kWh subsidies to charging stations.

4.2.3 Fixed Cost Recovery

A social planner would decide to build stations that increase social surplus even if they generate negative profits. No profit maximizing firm would choose to build a station that generates negative profits, so a better benchmark may be to require that stations recover fixed costs. In this case, the social planner sets prices but firms choose whether to build stations. Firms only build stations if they expect to earn positive profits, so the social planner must set prices high enough to justify entry. It is important to understand how the multi-product nature of stations and capacity constraints impact the efficiency of fixed cost recovery.

In the single-product case, the social planner would set a station's price equal to the average cost (Viscusi, Harrington and Sappington, 2018). That is, $p_i = c + \frac{K}{Q_i}$, the marginal cost plus a markup to recover fixed cost. Setting price above marginal cost creates deadweight loss from reducing consumption below the optimal amount. The amount of deadweight loss is a function of the size of the markup and demand elasticity. Holding the markup constant, as demand becomes more elastic, consumption falls further from the efficient quantity.

In the two-period context, the social planner chooses $(\mathrm{P_P}, \mathrm{P_{O\text{-}P}})$ to maximize social surplus subject to the restriction:

$$(\mathrm{P_P} - \mathrm{MC_{Oper.}}) \cdot \mathrm{Q_P} + (\mathrm{P_{O\text{-}P}} - \mathrm{MC_{Oper.}}) \cdot \mathrm{Q_{O\text{-}P}} - K \geq 0. \tag{3}$$

The more elastic demand is for a good, the more a price increase will decrease quantity and therefore social surplus. It is more efficient then to recover fixed costs by applying larger markups to more inelastically demanded products (Ramsey, 1927). The set of linear prices that minimize deadweight loss while recovering fixed costs, often called "Ramsey prices," sets markups proportional to elasticities of demand across products (Boiteux, 1960; Baumol and Bradford, 1970).

Capacity constraints allow the station to recover some fixed costs without creating deadweight loss. Consider the case where $(\mathrm{P_P^*} - \mathrm{MC_{Oper.}}) \cdot \bar{\mathrm{Q}} \geq K$ and the station satisfies Equation (3). It can set prices at the efficient levels, $(\mathrm{P_{O\text{-}P}^*}, \mathrm{P_P^*})$, while recovering fixed costs. Alternatively, if $(\mathrm{P_P^*} - \mathrm{MC_{Oper.}}) \cdot \bar{\mathrm{Q}} < K$, the station will need to raise prices. It must recover the remaining $\hat{K} = K - (\mathrm{P_P^*} - \mathrm{MC_{Oper.}}) \cdot \bar{\mathrm{Q}}$ using Ramsey markups above $(\mathrm{P_P^*}, \mathrm{P_{O\text{-}P}^*})$. In the latter case, fixed cost recovery introduces deadweight loss, but it is smaller than it would be without capacity constraints.

An alternative method of fixed cost recovery is two-part tariffs. A network could set prices at or near the efficient prices and extract consumer surplus by requiring subscription fees. By

keeping the prices close to the social surplus, this approach creates less deadweight loss than Ramsey prices (Feldstein, 1972; Littlechild, 1975). While I omitted two-part tariffs from the profit-maximizing firm's considerations in Section 4, using two-part tariffs increases a monopolist's profits above those using linear prices (Oi, 1971). Networks offer subscribtions, so they have the ability and potential incentive to use two-part tariffs.

When capacity constraints allow efficient prices to recover fixed costs, two-part tariffs offer no additional efficiency gain. Two-part tariffs can eliminate deadweight loss only when efficient prices do not recover fixed costs and Ramsey prices induce deadweight loss. As $\hat{K}$ increases, two-part tariffs provide larger social surplus gains. The effect of an increase in $\hat{K}$ is mediated by the elasticity of demand; when demand is more elastic, markups create more deadweight loss. Therefore, the social surplus benefit of two-part tariffs depends on both capacity constraints and elasticity of demand.

In a competitive market, the number of firms, capacity constraints, and fixed costs can all lead to markups. Alternatively, extreme product differentiation or rigid consumer preferences could reduce substitution and allow networks to act as monopolists. I turn to the data to address whether high markups reflect competitive market conditions or suggest monopolist behavior. Section 5 addresses whether networks compete on prices and whether market entry reduces prices. In Section 7, I return to capacity constraints and fixed costs as possible explanations and compare observed prices to those that the efficient prices initially discussed in this section. I also show the relative efficiency of Ramsey prices in the fast charging market.

5 Impact of Station Entry on Incumbent Stations

In this section, I estimate the impact of station entry on incumbent prices, quality, and charging volumes. This combination of outcomes allows me to test for different forms of competition. If stations respond to competing-network entry by lowering prices, this aligns with the model of Bertrand competition amongst partially differentiated stations. If they do not lower prices but do improve quality, this would suggest stations are competing on quality but not price (they could also compete on both).

There are multiple reasons stations might not adjust prices or quality in response to competing-network entry. First, if there is no response and incumbent stations sell lower quantities following competitor entry, this indicates that networks do not profit maximize with linear prices. One explanation would be that they use two-part tariffs and have already set prices as low as maximizes social surplus. Another explanation is that supply-side frictions lead to sub-optimal firm behavior (Arcidiacono et al., 2020). Second, if there is no change in quantities, prices, or quality, then networks do not compete at the station level

because consumers do not substitute between networks. Such a result would indicate that either consumers do not view different networks as substitutes or that search costs or other demand-side frictions deter cross-network substitution.

5.1 Empirical Design

I consider the effect of station entry on incumbent charging quantities, prices, and quality. 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 operational costs are below their expected revenues. This means that the exact timing of entry is determined by administrative and technical factors rather than market conditions. My identifying assumption, that stations do not control the exact timing of entry, is the same that Arcidiacono et al. (2020), Davis, McRae and Seira (2025), Taylor and Muehlegger (2025), and others use.

My primary empirical approach is a stacked difference-in-differences event study model. Station construction is public, so a key threat to causal identification is anticipation. If stations lower prices in anticipation of station entry, then a standard difference-in-differences approach that averages pre-period prices would underestimate the counterfactual price in the absence of entry and bias the difference-in-differences estimate. I use an event study specification to show trends during the twelve weeks prior to station opening and disaggregate results by the number of weeks from treatment. This approach also has the benefit of showing how long it takes for quantities and prices to adjust. Finally, the stacked difference-in-differences approach resolves the negative-weighting and forbidden-comparison problems inherent in two-way fixed effects Baker, Larcker and Wang (2022); Gardner (2021).

I define treated stations as those within a five-minute drive of an entrant.[17] I match treated stations to untreated stations to create a counterfactual for outcomes in the absence of openings. I designate untreated stations as those that did not have an opening within a 10-minute drive within 24 weeks of the treatment opening. I limit matching to untreated stations operated by the same charging network, in the same core-based statistical area (CBSA), and with a similar number of nearby stations.[18] The goal of this approach is to compare treated stations to stations that were affected by the same market trends and faced a similar amount of competition prior to the entry event. The k counterfactual stations

[17] I explain the role of distance in Section 5.2.6 and provide results using a 10-minute threshold in Appendix A.

[18] I require the number of nearby stations at matched stations to be within one when the treated station has four or fewer nearby stations, within two when the treated station has five to nine nearby stations, or within three when the treated station has 10 or more nearby stations.

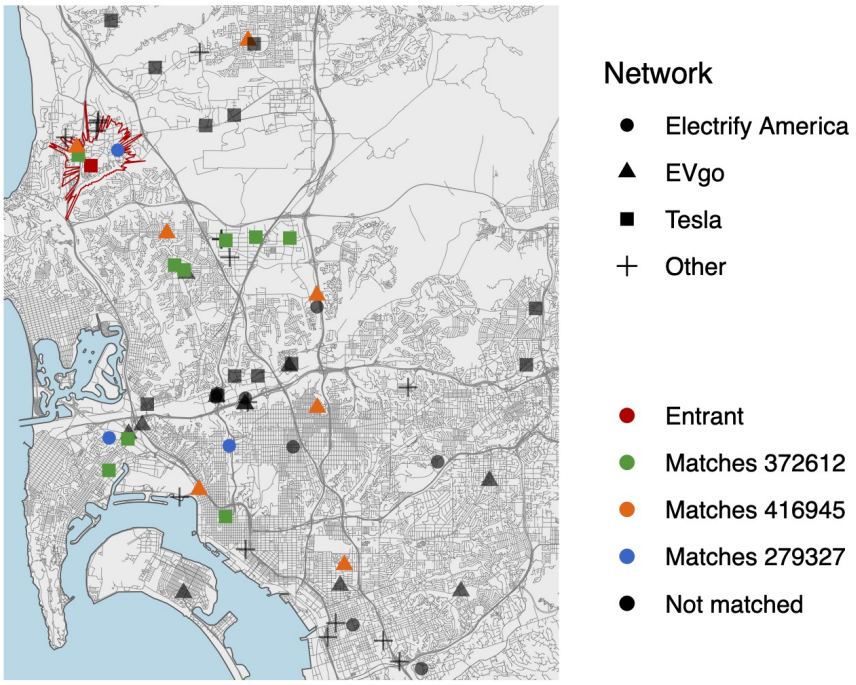


Figure 6: Visual Example of Matching Process

for each treated station are given a weight of $\frac{1}{k}$ to ensure each treatment event is weighted equally.

I provide a visual representation of this process in Figure 6. In this example, a new Tesla station (red circle) opens within a five-minute drive (depicted by the red line) of a Tesla (green circle), Electrify America (blue square), and EVgo (orange triangle) station. Each of those stations is matched to all the corresponding stations that are the same color and shape as the treated station. Those stations are all part of the same charging network, in the San Diego-Carlsbad CBSA, and near a similar (within one) number of stations. The map illustrates why I require nearly the same number of nearby stations for control stations. When electricity rates fall and marginal costs decrease, EVgo might lower prices at the orange triangle stations but leave prices unchanged where it has little competition, such as its station on Coronado Island, a black triangle towards the bottom left of the figure.

The event study runs from twelve weeks before entry to twelve weeks after entry. I avoid overlapping treatment by restricting to only entrances near an incumbent without another nearby entry event within 24 weeks. I consider incumbent electricity use, price, and health index as outcomes and run regressions separately for each network for quantity and price in case driver behavior and incumbent strategies vary by network.[19] I estimate the equation:

[19]For regressions with health index as the outcome variable, I present results aggregated across all networks due to my data sharing agreement.

$$y_{ihw} = \sum_{\tau=-12}^{\tau=12} \beta_{\tau d} \mathbf{1}[\text{EventWeek}_{iw} = \tau] \times \mathbf{1}[\text{Treated}_i] + \mu_{ih} + \gamma_{n(i)w} + \lambda_{u(i)m(w)} + \varepsilon_{ihw} \quad (4)$$

where τ represents event week and $\mathbf{1}[\text{Treated}_i]$ is a dummy variable equal to one for incumbents exposed to entrants and zero for the counterfactual group. I estimate station price and usage at the station-week-hour level to account for different prices and charging over the course of the day. I include station-hour fixed effects, μ_{ih}, to control for time-invariant station characteristics, network-week fixed effects, $\gamma_{n(i)w}$, to control for network pricing behavior over time, and utility-month of sample fixed effects, $\lambda_{u(i)m(w)}$, to capture changes in marginal costs over time. I estimate the impacts of opening on health index at the staion-week level and therefore include station fixed effects instead of station-hour fixed effects.

I take a number of steps to avoid potential bias. I set a 24 week threshold between entry events to ensure that no station-week in my analysis is treated by multiple entries. In these cases, I drop all entry events to ensure the pre- and post-periods are not contaminated. Following the modern difference-in-differences literature, I drop already-treated stations from the set of potential control stations to avoid violating parallel trends (de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021).

I apply two-way clustered standard errors at the CBSA and year-month level, because 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 (Cameron and Miller, 2015). The total number of clusters ranges from 51 to 59 across analyses.

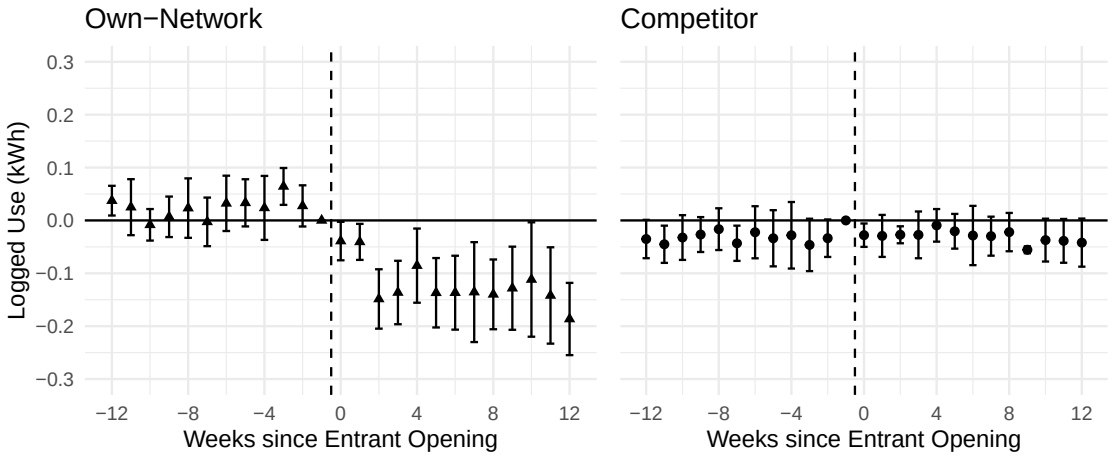
In addition to the event study models, I also estimate a standard difference-in-differences model. This model uses the same data but groups the twelve pre-entry weeks into a single pre-period group and the week of entry and following twelve weeks into a single post-period group. The difference-in-differences estimator recovers the change in the difference between the treatment and control group from before to after entry.

5.2 Results

5.2.1 Charging Quantities

Market entry has asymmetric effects on own- and competing-network stations. Figure 7 shows that charging at existing stations decreased following own-network entry but remains unchanged following competing network entry. The decrease from own-network entry occurs

shortly after station entry and is sustained for the event study's twelve week window at around a 14% decrease from just before entry. Figure A.3 shows the own-network effect is driven by Tesla stations and Figure A.4 shows the effect of competitor entry on charging is null across all networks. I provide results from the difference-in-differences model for these and the following event study analyses in Table A.2.



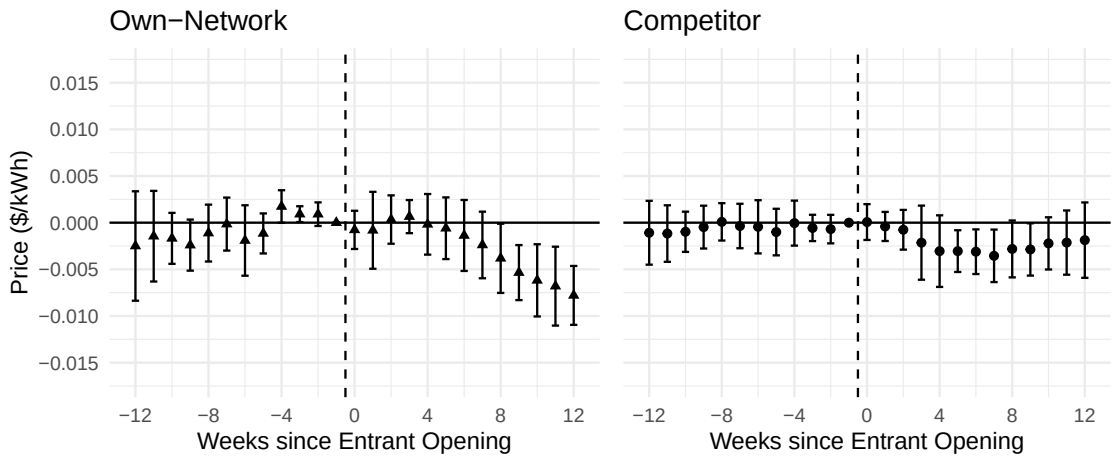
Notes: Data are station-week-hour electricity consumed for charging at each station and span January 2022 - December 2025.

Figure 7: Event Study Estimates of Own-Network Station Entry within Five Minutes on Incumbent Hourly Electricity Consumption

5.2.2 Prices

Price responses generally align with changes in charging volumes. Figure 8 shows no anticipatory price changes in the twelve weeks before a station's opening. After station entry, prices fall slightly at own-network stations but not competing stations. Again, the own-network effect comes from Tesla stations and the non-response to competitor entry is consistent across networks (see Figure A.5 and Figure A.6).

The use results showed that Tesla's new stations cannibalize some demand from any nearby incumbents, shifting demand down and leading to a lower optimal price. The gradual decrease does not reflect Tesla changing prices repeatedly, but rather that Tesla rarely changes prices, so the price change may lag the demand change by a couple weeks or months depending on when the network next updates prices. Similarly, stations experience no decrease in demand following competitor entry and therefore have no incentive to lower prices. The difference-in-differences results in Table A.2 suggest I can rule out average competitor price responses greater than 0.4 cents and network-specific prices responses greater than 0.7 cents. Using the average price and marginal electricity cost for the stations in the PG&E



Notes: Data are station-week-hour prices and span October 2024 - May 2026.

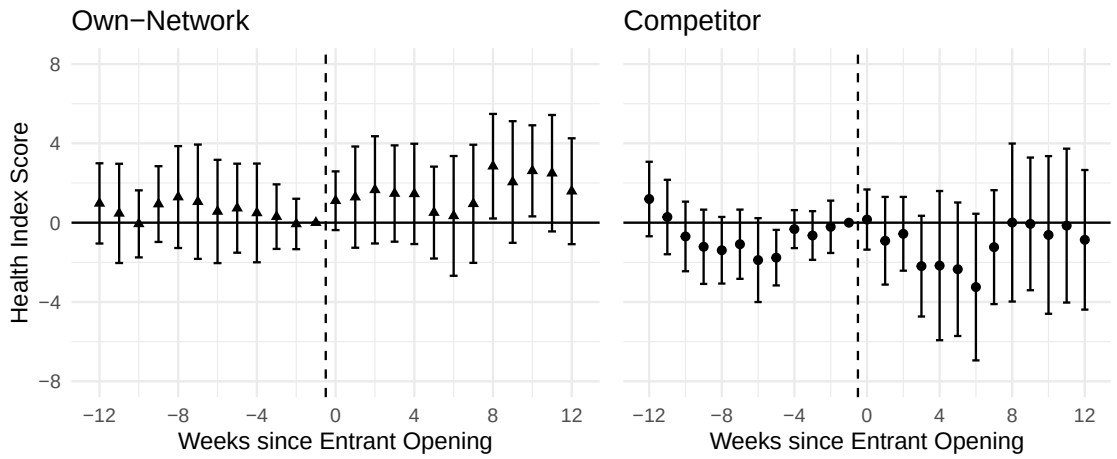
Figure 8: Event Study Estimates of Own-Network Station Entry within Five Minutes on Incumbent Price

data, the confidence interval bound of 0.4 cents maps to 1.5% of price minus marginal operating cost margins. Therefore I can rule out price decreases in the realm of the 6-7% estimated for the retail gasoline industry (Taylor and Muehlegger, 2025; Davis, McRae and Seira, 2025).

5.2.3 Quality

I also find no evidence that incumbent stations improve quality in response to greater competition. Figure 9 shows the effect of station entry on own-network and competing station health index score. Taken together, the price and quality results show stations do not appear to respond to compeitor entry. This is a rational decision – I detect no change in demand for stations following competitor entry, so the optimal prices and quality after entry should be the same as prior to entry. It is still possible that stations compete on other measures, or that competition is at the network level – networks make decisions on prices and quality that affect all stations in an area at once. I explore network-level pricing in Section 7.

My results suggest that networks do not compete on prices or quality at the station level. There is no incentive for them to do so, because consumers do not substitute across network to new stations. This combination of results suggests that consumers choose between the stations in a network rather than all stations. It is possible that networks or stations are highly differentiated (due to strong network or nearby amenity preferences) or that demand-side frictions reduce cross-network substitution and deter competition. This result does not



Notes: Data are for station-week health index score and span October 2024 - May 2026. Health Index Score is measured out of 100.

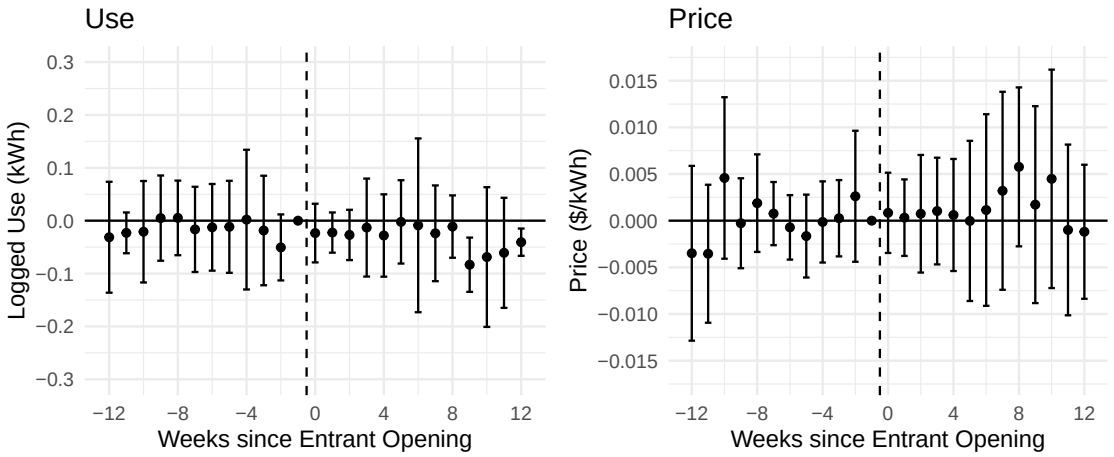
Figure 9: Event Study Estimates of Station Entry within Five Minutes on Station Quality

rule out that networks compete at a broader geographic level such as across the CBSA or state. It is possible that networks change prices in a competitive way periodically at all stations, that consumers choose between networks based on prices or quality, and that once they've chosen a network, consumers do not search outside of their network. Panel A of Figure 2 shows that networks do not change prices in response to other networks' price changes, so if networks do compete at a broader geographic level, such price competition is not dynamic.

5.2.4 Mediating Effect of Charging Standards

One possible explanation for why I detect no cross-network substitution is that different networks use different charging standards. Almost all cars are only equipped to charge with one charging standard, so drivers must either go to a station with that standard or own the requisite adapter. Prior to 2025, Tesla drivers charged at Tesla stations and non-Tesla drivers charged at non-Tesla stations. Since 2025, Tesla's NACS plug has adopted more widely. Some automakers switched to NACS, non-Tesla networks built new stations with NACS plugs and retrofit old stations to include NACS plugs (though the latter is not common), and non-Tesla manufacturers began to make NACS adapters available to drivers. These changes may have reduced the differentiation between Tesla and non-Tesla stations.

I use three approaches to evaluate whether the lack of substitution across networks reflects preferences for charging standards rather than networks. First, I run the same usage event study for competitor entry as in Section 5.2.1 but limit to just entrants using the same charging standard as the incumbent. The changes in charging standards and converter



Notes: Data are station-week-hour electricity consumed and price for charging at each station and span January 2022 - December 2025 and October 2024 - May 2026, respectively.

Figure 10: Event Study Estimates of Entry by Competing Station with Same Charging Standard within Five Minutes

accessibility in 2025 motivate two additional experiments. The first is to limit the window of analysis to 2025 onwards. If non-Tesla networks begin competing with Tesla for customers in 2025 now that more non-Tesla stations had NACS plugs and more non-Tesla drivers had NACS adapters, focusing on just the period with competition should reveal an impact of competitor station openings. Second, my weekly panel of station information allows me to determine when networks retrofitted existing stations to add NACS chargers. I use the same event study approach to determine whether charging volumes or prices at nearby existing Tesla stations change following addition of NACS chargers.

Figure 10 shows that there is no substitution across stations from different networks that have the same charging standard and stations still do not lower prices. I provide results by network for use and price in Figure A.7 and Figure A.8, respectively. Additionally, there is no substitution from Tesla stations to non-Tesla stations when the non-Tesla stations add NACS chargers (see Figure A.9) or to new non-Tesla stations in 2025 when these stations are potentially better substitutes (see Figure A.10). These results suggest it is network rather than charging standard differences that drive the lack of substitution across networks. One potential explanation is that drivers do not consider all possible stations with the charging plug type they need, but instead open one network's application to look for nearby stations.

5.2.5 Capacity

When a station is capacity constrained, its marginal cost curve becomes vertical. The optimal price it can charge is greater than in the absence of the capacity constraint because it raises prices to clear the market rather than increasing quantities. My finding that Tesla lowers incumbent prices after it opens a new station nearby may indicate then that Tesla opens stations to relieve capacity constraints at existing stations.

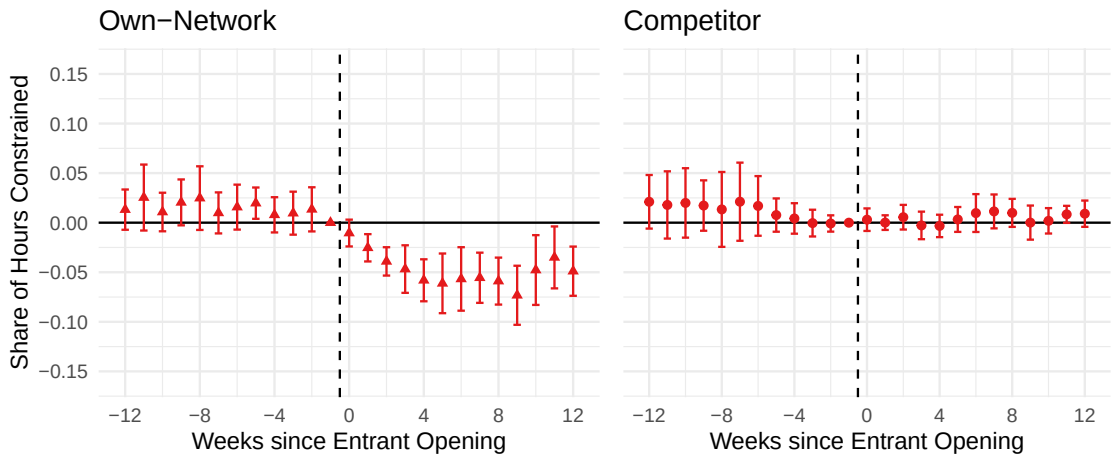
I use the same event study approach from the prior entry analyses to test whether entry relieves capacity constraints. Ideally I would define a station as capacity constrained during any hour where the station must reduce the amount of electricity drawn by each charger or all chargers are in use. I cannot observe either in my data, so I use a rough measure of how close electricity discharge is during an hour to the maximum amount of electricity the station can discharge. I calculate the observed electricity usage during any given hour during the station's history and designate an hour as potentially capacity constrained (at or near capacity) if electricity consumption during that hour is at least 80% of a benchmark for the maximum feasible amount of electricity consumption. I set that benchmark as each station's 98^{th} percentile of electricity consumption during daytime charging hours.[20] Using this approach, I classify 5.4% of station hours as capacity constrained.

The events study results in Figure 11 show that Tesla stations exposed to new own-network stations significantly reduce the likelihood of capacity constraints. The probability of a Tesla station being potentially capacity constrained decreases by 6.6 percentage points. This estimate is very large in magnitude – a 47% decrease from the 14 percent of pre-period hours classified as potentially capacity constrained. This suggests stations may lower prices following nearby own-network entry because they are less likely to be capacity constrained.

5.2.6 Distance

In the previous models, I limit treatment to the effect of openings within five minutes and compared to similar stations without any openings within ten minutes. In this section, I test this assumption on the distance over which consumers are willing to substitute between stations. I compare stations treated by openings that are 0-5 minutes, 5-10 minutes, and 10-15 minutes away to control stations without any openings within a 15-minute drive. I focus specifically on the effct of Tesla openings on Tesla incumbents as this combination of

[20] Charging speeds vary by car model and the car battery's charge level (charging gets notably slower once the battery is more than 80% full – Electrify America doesn't allow charging past 85% at some stations and Tesla charges extrea for cars charging above 80%) so there is no set amount of electricity a fully occupied station would discharge. I therefore use the 98^{th} percentile of charging from 8 AM to 8 PM to rule out hours where cars were exceptionally fast in terms of charging speeds. Changing this threshold up or down makes a slight difference in the share of hours classified as at capacity, but no difference in the relative effect size.



Notes: Data are total hourly electricity consumption at each station and span January 2022 - December 2025.

Figure 11: Event Study Estimates of Station Entry within Five Minutes of Tesla Station on Share of Hours near Charging Capacity

existing and new stations was the one with the largest magnitude estimates.

I increase sample size for the analysis of the effect on charging quantities by shrinking the analysis window to eight weeks before and after opening. The results in Figure 7 show that the effect of entry on charging quantities is stable after two weeks, so changing the window should not be a concern for the parallel trends requirement. The effect on prices in Figure 8 doesn't materialize until six to eights weeks after opening and continues to grow through the study period, so I do not change the analysis window for the price analysis.

I present results for the effects of own-network openings on incumbent Tesla stations in Figure A.11. The effect of new Tesla stations on nearby existing Tesla station charging quantities is largest for the 0-5 minute treatment group, but also negative and significant for the 5-10 minute treatment group. Even though there is no effect on charging for stations 10-15 minutes away, all three groups decrease prices following entry. This could reflect that Tesla is decreasing prices in anticipation of a demand response, but it doesn't materialize for the stations 10-15 minutes away. Because my results suggest that drivers are willing to switch to new stations 5-10 minutes away from an existing station, I conduct all event studies in this section using a 10-minute treatment window and provide those results in Appendix A (see Figure A.12-Figure A.16).

6 Demand Estimation

6.1 Model

The results in Section 5.2 show that consumers do not substitute to new stations from different networks. However, they do not answer whether consumers respond to prices. To answer this question and whether consumers substitute across time of day, I estimate a model of heterogeneous demand.[21]

EV drivers must regularly choose where and when to recharge their vehicles. Preferences for charging location are likely based on a variety of factors including price, proximity, nearby amenities, time of day, charging speed, and reliability.[22] Importantly, those preferences are likely to be heterogeneous across consumers. Therefore, my model builds on the framework for estimating models of discrete choices across heterogeneous consumers developed by Berry (1994) and Berry, Levinsohn and Pakes (1995).[23]

In each period t in market m, consumers choose when and where to charge their electric vehicle.[24] Consumer i's indirect utility from charging their vehicle at a certain station during a specific hour, jointly denoted as product j, is given by the equation:

$$u_{ijt} = x_{jt}\beta_{it} - \alpha_{it}p_{jt} + \xi_{jt} + \varepsilon_{ijt} \tag{5}$$

where α_{it} and β_{it} reflect preferences over prices, p_{jt}, and a vector of other observable station characteristics, x_{jt}, respectively. ξ_{jt} captures the utility from station-hour attributes that are observed by consumers and the network but not the econometrician.[25] Indirect utility

[21] The standard approach to estimating models in the style of Berry, Levinsohn and Pakes (1995) includes both estimating consumers' preferences and suppliers' marginal costs. I observe electricity costs and therefore do not include a supply side in the model to estimate marginal costs.

[22] Networks have periodically offered free charging with the purchase of a car, which could lead to some consumers having perfectly inelastic demand with respect to price. Using California registration data, I estimate that the share of EV owners with free charging in 2025 could be 9%. However, I expect that it is notably lower as many of these offers were limited to a relatively low amount of free charging.

[23] I make three assumptions to consider charging quantities in a discrete framework. First, I make the same assumption as Nevo (2001), that consumers do not gain utility from consuming from multiple chargers. Their decisions can be seen as multiple purchase instances that are independent of each other, which avoids the need to model consumption as a continuous variable. Second, I assume that the choice set does not impact the amount that consumers drive. The total amount of gasoline purchased is highly inelastic, which is in line with this assumption: if the price of driving decreases, consumers will still drive the same amount. Third, I assume that consumers have decided on an optimal amount to charge before choosing their charging station. This is similar to Hendel (1999), who models firms buying multiple units of several brands of computers as making the optimal choice on many tasks, which in aggregate yield the observed purchase.

[24] No station hour can be in two markets, so I do not include m in notation because it is fully determined by station hour j.

[25] For example, suppose a charging station is located in the parking lot of a grocery store and the grocery

also includes individual preference shocks ε_{ijt}. I assume ε_{ijt} are i.i.d (across (i, j, t)) draws from a type I extreme value distribution, and are observed by neither the econometrician nor network. This specification yields the mixed Logit model.

The mixed Logit allows preferences to vary across consumers and time. For example, individual i's preferences over price and observable characteristic k are given by the following two equations:

$$\beta_{it}^{(k)} = \beta_0^{(k)} + \beta_\nu^{(k)} x_{jt}^{(k)} \nu_{ik} \tag{6}$$

$$\alpha_{it} = \alpha_0 + \alpha_\nu \nu_{ip} \tag{7}$$

where β_0 and α_0 measure average utility across all consumers and the terms $\beta_\nu^{(k)} x_{jt}^{(k)} \nu_{ik}$ and $\alpha_\nu p_{jt} \nu_{ip}$ capture deviations in preferences from the population average. It is convenient to rewrite the utility as a function of average and individual preferences:

$$u_{ijt} = \delta_{jt} + \mu_{ijt} + \varepsilon_{ijt} \tag{8}$$

where δ_{jt} is the mean utility consumers receive from choosing to charge at station-hour j during period t, and μ_{ijt} is the individual (mean zero) deviation from that mean utility. I decompose the mean utility term into both observed and unobserved components:

$$\delta_{jt} = x_{jt}\beta_0 - \alpha_0 p_{jt} + \xi_{jt} \tag{9}$$

where β_0 and α_0 reflect average utility from x_{jt}, a vector of K observable characteristics, and p_{jt}, the price per kWh of charging, respectively. ξ_{jt} captures the impact of unobserved station-hour attributes on utility. The individual deviation can be expressed as:

$$\mu_{ijt} = \sum_K \left[\beta_\nu^{(k)} x_{jt}^{(k)} \nu_{ik}\right] - \alpha_\nu p_{jt} \nu_{ip} \tag{10}$$

where K is the vector of observable characteristics. For simplicity, I will instead write $\mu_{ijt} = (x_{jt}, p_{jt}) \cdot \Sigma \nu_{it}$ where Σ is a $(K+1) \times (K+1)$ diagonal matrix with the diagonal

store goes out of business. The station may anticipate reduced charging demand and respond by lowering prices. The econometrician would underestimate the price elasticity of demand because they would assume that the change in quantity was purely a function of the price change (if no other characteristics changed).

$(\alpha_\nu, \beta_\nu^1, ..., \beta_\nu^K)$ and ν_{it} is the vector of individual preference shocks.

Consumer i chooses to charge at station-hour j in period t if $u_{ijt} \geq u_{ikt}$ for all $k \neq j$, $j, k \in m$. One possible k is the outside option, charging at a slower charger or station not in my data, which gives utility $u_{i0t} = \varepsilon_{i0t}$. That is, consumers choose the station-hour that gives them the highest utility of all station-hours in market m during period t, unless this is less than the utility from the outside option.[26] Integrating over all consumer choices using the distribution of consumer preferences, $F(\nu_{it})$, yields the market share for each station-hour:

$$s_{jt} = \sigma_j(\boldsymbol{\delta}_t, x_t, p_t; \Sigma) = \int \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{k=1}^{J} \exp(\delta_{kt} + \mu_{ikt})} dF(\nu_{it}) \tag{11}$$

where $\boldsymbol{\delta}_t = (\delta_{1t}, ..., \delta_{Jt})$, $x_t = (x_{1t}, ..., x_{Jt})$, and $p_t = (p_{1t}, ..., p_{Jt})$.

6.2 Estimation

The goal of estimation is to recover the vector of parameters $\theta = (\alpha_0, \beta_0, \Sigma)$. One could theoretically estimate the parameters by minimizing the distance between the observed and predicted market shares. However, such an approach does not account for the correlation between prices and unobserved product characteristics, ξ_{jt}. To handle potential correlation, I implement the approach used by Berry, Levinsohn and Pakes (1995).

The first step is to recover mean utility, δ_{jt}, for each product and time. The presence of ξ_{jt} means I cannot estimate β_0 and α_0 directly and instead calculate mean utility. Berry (1994) and Berry, Levinsohn and Pakes (1995) show that one can fix the elements of Σ at predetermined values and invert the market shares to yield $\hat{\delta}_{jt} = \hat{\sigma}_{jt}^{-1}(\hat{s}_{1t}, ..., \hat{s}_{Jt}; \Sigma)$.

The second step is to regress $\hat{\delta}_{jt}$ on x_{jt} and p_{jt} to estimate α_0, β_0 using the equation $\hat{\delta}_{jt} = x_{jt}\beta_0 - \alpha_0 p_{jt} + \xi_{jt}$. However, ξ_{jt} are observed by consumers and the network but not the econometrician. ξ_{jt} likely impact prices and may be correlated with the observed variables x_{jt} (which are assumed to be exogenous), which would bias estimates of α_0, β_0. The solution is to use a vector of exogenous variables, $\boldsymbol{Z}_t$, to build a vector of instruments, z_{jt}, for p_{jt}. One can then estimate an instrumental variables regression to recover $\hat{\alpha}_0, \hat{\beta}_0$ (I explain my instruments in Section 6.2.1).

The estimation procedure explained so far relies on holding Σ fixed while one estimates β_0 and α_0. The identifying assumption for both the instrumental variables regression in the second step and estimation of Σ is $E\left[\xi_{jt} | \boldsymbol{Z}_t\right] = 0$, which implies $E[z_{jt}\xi_{jt}] = 0$ for any z_{jt} constructed from $\boldsymbol{Z}_t$. The empirical analogue for the n^{th} moment is $m^n(\theta) = \hat{E}[z_{jt}^n \xi_{jt}]$. One

[26] The majority of outside option charging is home charging, but the outside option also includes workplace charging and some charging at fast charging stations I do not observe.

can stack all the moment conditions to form $\boldsymbol{m}(\theta)$ and create the generalized method of moments (GMM) estimator:

$$\hat{\theta} = \arg\min_{\theta} \boldsymbol{m}(\theta)' W \boldsymbol{m}(\theta) \tag{12}$$

where W is a positive definite weighting matrix with dimension $N \times N$. Conlon and Gortmaker (2020) calculate a GMM objective $q(\Sigma) = \boldsymbol{m}(\theta)' W \boldsymbol{m}(\theta)$ (note that $q(\Sigma)$ does not include α_0, β_0, which are concentrated out from θ because, given each Σ, they have a closed-form solution). They continute to try new Σ until the gradient of q with respect to Σ is approximately zero and one can conclude that $\boldsymbol{m}(\theta)' W \boldsymbol{m}(\theta)$ has been minimized. At each guess of Σ, they repeat the first and second steps and evaluate $q(\Sigma)$.

Any positive definite W gives a consistent estimate of θ, but only one W provides efficient estimates. The efficient weighting matrix is the inverse of the asymptotic covariance matrix of the population moments. Therefore, in order to get the efficient estimates, one must solve the problem twice. The first solution yields a consistent estimator that is used during the second iteration to recover the efficient estimator.

I conduct the estimation process using the *PyBLP* Python package from Conlon and Gortmaker (2020), which is based on the approach developed by Berry, Levinsohn and Pakes (1995). I estimate the mixed Logit model with markets defined at the week by CBSA level.[27] CBSAs are spatially distinct and there are very few stations that have a nearby station not in their CBSA, so it is unlikely that consumers are substituting across CBSAs. I choose to divide use into weeks to match my price data and create more moments to match in the estimation process. Because prices change infrequently and with no regularity, I argue it is unlikely that consumers are considering cross-week substitution.

I include different vectors of station characteristics for (α_0, β_0) and Σ. I estimate homogeneous preferences for weekly price, reliability (station health over the prior four weeks), whether the station has a low, medium, or high health index score during the current week,[28]

[27] I drop CBSAs without at least ten stations, which leaves seven CBSAs and 56 weeks totaling 392 markets.

[28] I use the categorical variable in an attempt to control for the share of chargers that were operable during the week rather than the share of charging attempts that were successful. Both are included in the calculation of the health index, and the effect of a broken charger on the index should be larger than the effect of a failed charging attempt. Drivers can learn of broken chargers from mobile applications and choose to avoid a station whereas they will suffer failures to charge at the station and may choose to use another charger at the station. I observe clumping just below health index scores of 50 and 75 in the data, which I believe is indicative that there are a large number of cases where one or two of four chargers are broken for the entire week and there is some variation in the number of failed charges that pushes the scores just below the corresponding share of chargers that are functional (for a station with three functioning chargers and one broken charger, this would be 75% which I expect maps to a health index score of 75).

and station-hour fixed effects. I estimate heterogeneous preferences for time of day (morning: 6-9 AM, late morning: 9 AM - 12 PM, afternoon: 12-4 PM, early evening: 4-7 PM, evening: 7-11 PM, and overnight: 11 PM - 6 AM) and charging network.

6.2.1 Instruments

I build a vector of instruments that incorporates both cost and demand shifters. Price is endogenous to demand, so higher priced products likely also have higher market shares. Instruments allow the econometrician to isolate exogenous changes in price.

The goal of cost instruments is to capture the effect of marginal cost – rather than demand – on prices. I use the marginal cost of electricity that each station faces as an instrumental variable. This fully captures changes in marginal operating costs. There is variation in the marginal cost of electricity across hours and weeks, but there is very little within-week-hour across-station variation.

I rely on demand shifters to capture variation in exogenous price pressure across stations. My first set of demand instruments is a set of differentiation instruments, a geographical analog to those proposed by Gandhi and Houde (2020). I instrument for the number of own-network and competitor stations within 5-, 10-, 15-, and 20-minute rings of the station. These instruments are intended to account for the amount of differentiation and therefore price setting power a station has in the market. The final set of demand instruments is the price of residential charging at different times of the day to capture changes in relative preference for the outside option.

6.3 Results

I present estimates of the parameters from the model of consumer demand in Table 2. The homogeneous preferences (α, β) are calculated as the average preference across individuals. The average preference for price is negative and significant, suggesting general preferences for cheaper charging. These preferences are relatively small though. The average preference for reliability is positive and significant while the coefficients for stations with low or medium health scores are negative and significant. These results show that consumers value station functionality, which matches what one would expect. The implied willingness to pay for a 10 point increase in reliability (measured 0 to 100) is 2.6 cents and 16.8 cents for increasing the current week health index from below 50 to above 75.

Heterogeneous parameter estimates represent the standard deviation of preferences across individuals. The estimates for time of day all have large standard errors, which means I cannot rule out a large amount of heterogeneity in preferences for charging at different times

Table 2: Estimated Demand System Parameters

Homogeneous Parameters (α, β)	Estimate	(SE)
Price	-2.655^{**}	(0.648)
Reliability	0.007^{**}	(0.001)
Health Index < 50	-0.447^{**}	(0.041)
Health Index 50-75	-0.172^{**}	(0.016)
Heterogeneous Parameters (σ)		
Morning	-0.117	(56.307)
Late Morning	0.318	(129.797)
Afternoon	-0.930	(66.499)
Early Evening	0.451	(21.700)
Evening	-0.175	(36.180)
Overnight	7.671	(4.323)
Electrify America	0.338	(10.612)
Tesla	0.041	(8.970)

Notes: $*/**$ Denote significance at $p < 0.05/0.01$ level.

of day. The results for network preferences are similarly inconclusive. One would expect that all or most of the σ parameters should be large. The results in Section 5.2 suggest strong network preferences and we would expect consumers to potentially have rigid preferences for time of day as well. One possibility is that the lack of microdata or demographic data for fast charging consumers meaningfully reduces the precision of estimation. Additionally my data do not capture the true demand at an hour where consumption is capacity constrained.[29]

I aggregate individual preferences to calculate elasticities for each individual and then average elasticities across individual. The parameter estimates suggest that consumers have relatively homogeneous price preferences and are somewhat price sensitive. I present average own- and cross-price elasticities in Table 3. Average own-price elasticities vary across networks and time of day, with estimates ranging from -0.99 to -1.78 and an average elasticity of -1.33.[30] The confidence intervals for these estimates are fairly large; the average elasticity has a 95% confidence interval of -0.66 to -1.87 (I provide confidence intervals for all own-price

[29]The capacity constraint both censors and influences demand. I cannot observe individuals who would have charged if there had been more chargers, and some individuals may see that a station is busy and choose to charge somewhere else. Conlon and Mortimer (2013) develops a method for handling these types of cases, but without data on when chargers are occupied, I cannot implement it. It is not clear which direction unobserved demand would bias my results. The inclusion of station-hour fixed effects means that one might expect that a given station-hour is more likely to be capacity constrained when prices are lower. On the other hand, Figure 11 suggests networks may use prices as a rationing method meaning that demand would be underestimated at higher prices.

[30]I do not focus on differences between subscriber and non-subscriber prices because the difference is a constant multiplier, so switching from non-subscriber prices to subscriber prices would hold all percentage changes in prices constant.

Table 3: Average Own- and Cross-Elasticities

Network	Time	Own	Within Station-Time	Within Network	Within Time
EVgo	Morning	-1.5268	0.0006	0.0007	0.0013
EVgo	Late Morning	-1.5922	0.0012	0.0007	0.0029
EVgo	Afternoon	-1.7087	0.0019	0.0007	0.0053
EVgo	Early Evening	-1.7800	0.0014	0.0007	0.0039
EVgo	Evening	-1.6618	0.0008	0.0007	0.0020
EVgo	Overnight	-1.3681	0.0042	0.0013	0.0080
Electrify America	Morning	-1.6080	0.0015	0.0019	0.0013
Electrify America	Late Morning	-1.6062	0.0033	0.0019	0.0030
Electrify America	Afternoon	-1.6038	0.0057	0.0021	0.0056
Electrify America	Early Evening	-1.6055	0.0040	0.0019	0.0040
Electrify America	Evening	-1.6074	0.0021	0.0019	0.0021
Electrify America	Overnight	-1.6014	0.0081	0.0028	0.0084
Tesla	Morning	-1.0553	0.0015	0.0023	0.0013
Tesla	Late Morning	-1.1692	0.0036	0.0023	0.0029
Tesla	Afternoon	-1.1815	0.0070	0.0025	0.0055
Tesla	Early Evening	-1.1838	0.0050	0.0023	0.0039
Tesla	Evening	-1.1439	0.0026	0.0023	0.0020
Tesla	Overnight	-0.9887	0.0100	0.0035	0.0083

elasticity estimates in Table A.3). These estimates are in line with the -1 to -1.45 Bernard et al. (2025) find in the United Kingdom.[31]

I estimate that cross-price elasticities are very low, suggesting little willingness to substitute across stations or hours. For example, consider the case where a Tesla station raises the 12 PM price by 1% but does not change prices from 1-4 PM. My estimates indicate that 12-1 PM charging will decrease by 1.6%, but charging will only increase during 1-4 PM hours by an average of 0.007%. The cross-price elasticities decrease as stations and hours become further apart, but are not high even when comparing two adjacent hours at the same station or two nearby stations Figure A.17. This results in a large amount of diversion to the outside good, which is likely charging at a home or slower public charger. Taken together, the elasticity estimates suggest consumers are somewhat price sensitive but do not search for lower prices.

Elasticities vary across networks and time of day. The results suggest Tesla stations face

[31] Bernard et al. (2025) estimate headline elasticities of -2 to -2.9, but halve these elasticities to -1 to -1.45 to estimate the net demand change. The adjustment accounts for their setting, where they provide discounts through a mobile application, but consumers are not required to use the mobile application to pay at the charger. They halve their headline estimates because half of the headline estimate quantity increase coming from consumers who always charged at the station switching to payment using the mobile application with discounts.

more inelastic demand than EVgo and Electrify America stations. Overnight demand is more inelastic and substitution to other overnight hours is greater. This could reflect that charging during these times may disproportionately capture long distance driving, where the cost of delaying charging is greatest. Another explanation is that prices are lowest overnight, and the consumers who choose to charge at the cheapest and most inconvenient hours may have worse outside options, reducing their willingness to substitute away as prices increase (but remain the lowest of any hour). The latter explanation would suggest a form of nonlinearity in elasticities rather than a true preference for overnight charging.

7 Pricing Strategies and Efficiency

Descriptive evidence in Figure 1 shows large markups above marginal operating costs, and the empirical results in Section 5.2 suggest increasing the number of stations in the market does not decrease markups. It is important then to understand how efficient current prices are given they are unlikely to decrease as more stations enter. In this section, I expand on the theoretical framework from Section 4 and use the results from Section 6.3 to characterize observed prices and calculate their effect on social surplus.

7.1 Modified Ramsey Problem

I modify the Ramsey problem formulation from Crew, Fernando and Kleindorfer (1995) to account for capacity constraints. I include a condition that quantity demanded must be at or below the station's capacity, $\bar{X}$. I simplify this problem by writing it for a single charging station, but the network's problem is analogous.

During a day, a station supplies charging at a set of times (i.e. morning, afternoon, evening) $t \in 1, 2, ..., T$ with constant marginal cost for each given by c_t. Heterogeneous consumers each have demand for charging at different time periods, $\boldsymbol{x} = (x_1, ..., x_T)$, based on their individual valuation of consumption bundles, $V(\boldsymbol{x}, i)$, where i indexes consumers. The total demand for charging at time period t is the sum of individual demand, $x_t(\boldsymbol{P}, i)$, which is a function of all time period prices and individual preferences:

$$X_t(\boldsymbol{P}) = \int_I x_t(\boldsymbol{P}, i)di, \quad t \in 1, ..., T. \tag{13}$$

The constrained Ramsey problem is to choose the set of prices, $\boldsymbol{P}$, that maximize social surplus, $W(P)$, subject to capacity constraints and recovering fixed costs. I write this as:

$$\max_{\boldsymbol{P}} W(\boldsymbol{P}) = \int_I \Big[V(\boldsymbol{x}, i) - \sum_t P_t x_t(\boldsymbol{P}, i)\Big] di + \sum_t (P_t - c_t) X_t(\boldsymbol{P})$$
$$\text{s.t.} \quad \Pi(\boldsymbol{P}) = \sum_t (P_t - c_t) X_t(\boldsymbol{P}) \geq \Pi_0 \tag{14}$$
$$0 \leq X_t(\boldsymbol{P}) \leq \bar{X}, \quad \forall t \in 1, ..., T$$

where the two terms added together on the first line represent consumer surplus and station surplus, respectively. The two constraint conditions require that the station earn surplus to cover fixed costs and that the amount of charging cannot exceed capacity at any hour. Converting this maximization problem from an individual station to the network's price setting decision requires optimizing across all stations and times of day (t indexes station-times rather than just times at a single station) but otherwise does not change the problem.[32]

There are three possible forms for the solution to Equation (14). First, there is the case where the capacity constraint binds but the profit constraint does not. In all periods where demand intersects marginal cost on the vertical portion ($X_t(\boldsymbol{P}^*) > \bar{X}$), the station generates surplus of $(P_t - c_t)\bar{X}$, which sum to a value greater than Π_0. By raising prices to eliminate deadweight loss from misallocation, the network generates sufficient surplus to recover fixed costs and does not need to raise prices above the efficient prices. Second, if the efficient prices do not generate enough surplus and the capacity constraints do not bind on the unconstrained Ramsey prices, $\boldsymbol{P}^R$, the most efficient option is $\boldsymbol{P} = \boldsymbol{P}^R$. Third, if both constraints bind, the solution is to recover the fixed costs not covered from efficient pricing by applying Ramsey markups.

A limitation of my data is that there is no obvious way to define $\bar{X}$. In Section 5.2.5, I defined a station's maximum feasible draw as the 98$^{\text{th}}$ percentile of hourly daytime electricity consumption. Setting $\bar{X}$ at the maximum feasible draw multiplied by the number of hours (i.e. four afternoon hours per day times seven days per week) would require the station to operate with all chargers in use and little customer idling for a whole week. If there is a large amount of stochastic variation in demand, car types, or idling, then it's possible for the station to be well below that level and still run out of capacity regularly.[33] I therefore set $\bar{X}$ as 70% of maximum capacity over a period to account for variation in consumption. I discuss the implications of this choice when I present results in Section 7.2.

[32] I explain this the calculation process in Appendix C.2.

[33] It seems likely there is significant stochastic variation. Tesla has switched from time-of-use pricing to demand-based pricing, which would not be necessary if there was no stochastic variation in demand.

7.2 Characterization of Observed Prices

I use the elasticities of demand and observed prices, costs, and quantities to solve three optimization problems. I assume linear demand and calculate profit maximizing prices as the set of prices that maximizes the profit portion of Equation (14) subject to the capacity constraint. These are static profit maximizing prices that would only maximize profit if competition is not dynamic. I argue this is a valid approach because the results in Section 5.2 suggest stations do not compete on prices and Figure 2 shows networks do not follow each other's price changes.[34] Second, the social surplus maximizing prices are the set of prices that maximizes Equation (14) subject to only the capacity constraint. Third, the constrained Ramsey prices are the set of prices that maximizes Equation (14) subject to both the capacity constraint and restriction that the network recovers some amount of fixed costs.

I start by comparing observed prices to the sets of prices that maximizes profit and social surplus. Figure 12 shows the average prices and marginal cost by network and time of day. I show both the average observed price that a network's subscriber would pay and that a driver without a subscription would pay. Across all networks and times of day, the average observed non-subscriber price is similar to the average profit maximizing price.[35] That modeled profit maximizing prices are consistent with observed behavior that one would expect to be profit maximizing provides a measure of validation for the demand estimation results.[36]

The difference between marginal operating costs and welfare maximizing prices reflects capacity constraints.[37] If a station is not at capacity at a given time, then the social surplus maximizing price is equal to the marginal operating cost. When the station faces capacity constraints, marginal cost becomes vertical and the social surplus maximizing price is the price that equates quantity demanded and maximum capacity.

A second result evident in Figure 12 is that subscriber prices are generally above the welfare maximizing prices. Additionally, there is much more within-day variation in welfare maximizing price than in observed prices. Network behavior is not consistent with using two-part tariff pricing. An important comparison then is between observed prices and the

[34] The results in both Section 5.2 and Section 6.3 show minimal consumers substitution across networks, so making the model dynamic would have little downward pressure on prices.

[35] The one exception to this is overnight at Tesla stations, when demand is more inelastic and prices are low. It is possible prices are lower to encourage consumers to switch from peak-demand hours to overnight hours or to avoid displeasure from consumers on roadtrips who need to charge overnight. Given that few drivers charge overnight, there is relatively little revenue to be made from raising prices during those hours.

[36] Networks that are vertically integrated may want to maximize profits across two vehicle sales and charging. However, they generally provide at least two years of free network subscription (access to the subscriber prices) with the purchase of their vehicles, so they should would use the subscriber price as part of the vertical integration strategy.

[37] I show in Figure A.18, that changing the capacity threshold from 70% to 60% or 80% of feasible maximum charging changes welfare maximizing prices by a few cents.

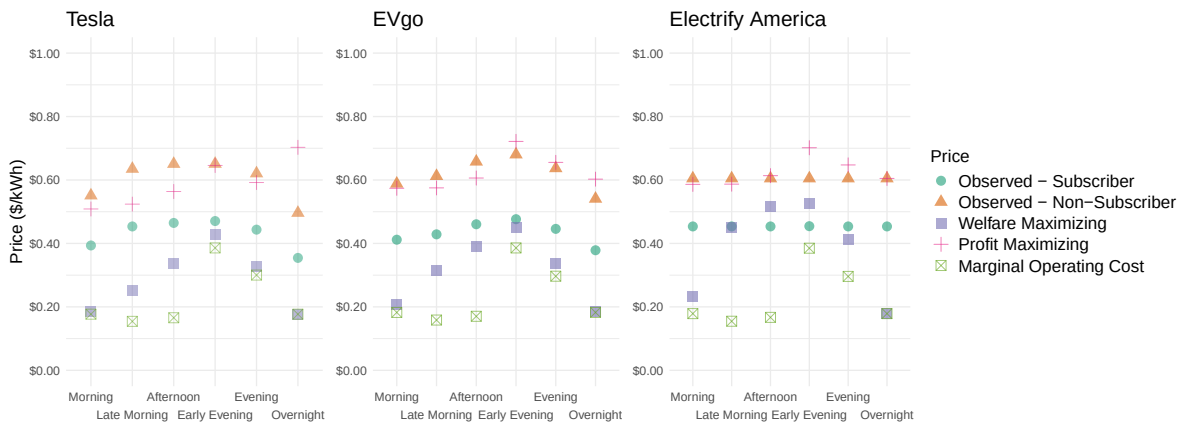


Figure 12: Comparison of Observed and Profit and Social Surplus Maximizing Prices

linear prices that produce the greatest social surplus while still recovering a station's fixed costs, the Ramsey prices. If prices are notably above the Ramsey prices, then there is room to increase social surplus by decreasing prices.

7.2.1 Fixed Cost Recovery

I do not observe the cost of building or maintaining stations, so I consider a range of fixed cost assumptions. Tesla claimed in 2025 that their average cost to build a station was about $40,000-45,000 per charger (Miyatra, 2025), which I use as a low-end construction cost estimate because it is lower than academic estimates (Gamage, Tal and Jenn, 2023; Li, 2023). As the upper end, I use the 75$^{\text{th}}$ percentile of National Electric Vehicles Infrastructure (NEVI) site cost per charger, which is $233,000 (McDonald, 2024). I use the 75$^{\text{th}}$ percentile because NEVI funding was limited to stations on designated alternative fuels corridors, which are likely to require more grid upgrade and construction costs than the stations in my data.

The AFDC estimates maintenance costs at about $400 per charger month (AFDC, 2023) and I assume that stations pay monthly capacity charges for 100 kW per charger at the low end and 300 kW per charger at the high end. Using a frequently assumed lifespan of 10 years and discount rate of 6%, I calculate the net-present value of lifetime costs as $94,000 under the low-end estimate and $319,000 under the upper-end estimate. For reference, Li (2023) and Gamage, Tal and Jenn (2023) estimate per charger costs at $152,000-302,000 and $122,000-440,000, respectively. My fixed cost estimates are slightly lower, which partially reflects that the stations in my sample are notably larger (9.9 chargers per station) than those in Li (2023) (1.7 chargers per station) and Gamage, Tal and Jenn (2023) (1.5 chargers per station). I translate my bounds to weekly costs and set the amount of fixed-cost recovery for the low, medium, and high fixed cost scenarios at $180, $400, and $620 per charger per

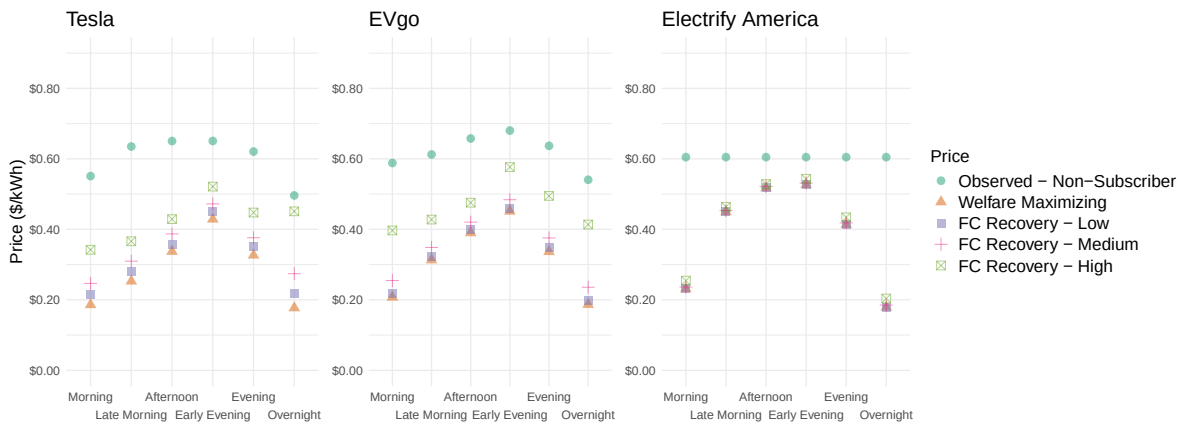


Figure 13: Comparison of Observed and Ramsey Prices

week, respectively.

My results suggest there is room for networks to lower non-subscriber prices while still recovering fixed costs. Figure 13 shows average observed non-subscriber prices and constrained Ramsey prices under different fixed cost assumptions. I plot non-subscriber prices rather than subscriber prices because I assume networks capture some benefits from subscribers through subscription fees or vertical integration that are not observed in the per-kWh prices. The difference between observed and Ramsey prices grows nonlinearly as fixed costs increase. At low fixed costs, nearly all stations can recover prices with market-clearing prices. As assumed fixed costs increase, a greater share of stations must apply additional markups to recover fixed costs. Under the medium fixed cost assumption, Ramsey prices are generally similar to efficient prices and at least 10 cents below non-subscriber prices.

My results suggest that not all stations would successfully recover fixed costs under these scenarios. I do not incorporate subsidies in my calculation, which likely explains this result. Figure A.19 shows that while all Electrify America and the vast majority of Tesla stations recover fixed costs across all three scenarios, less than two thirds of EVgo stations can recover high fixed costs. The difference between EVgo and the other two networks may reflect that their stations are more likely to have lower fixed costs. EVgo stations often use lower powered chargers, which are cheaper to build. Additionally, EVgo has received more subsidies than Tesla and Electrify America by an order of magnitude – California has awarded more fast charging subsidy funding to EVgo than any other company. Subsidies reduce the network's fixed costs, potentially even below the low fixed cost scenario.

I plug the Ramsey prices back into the demand estimation model to calculate the effects on surplus. I estimate that charging the Ramsey prices instead of observed prices would increase social surplus by 8-10% depending on the fixed costs. The increase to consumer surplus is much larger (42-133%), with slightly less than half coming from recovered dead-

weight loss. The remaining increase is a large transfer of surplus from producers, who lose 14 to 33% of observed surplus. This transfer would reduce networks' incentives to build stations and could hinder EV adoption targets.

No network appears to follow a two-part tariff or vertical integration strategy. Two-part tariffs are more efficient than linear prices for fixed-cost recovery and often notably reduce deadweight loss. Figure 13 shows that under low and medium fixed cost assumptions, the optimal linear prices are almost equal to the efficient prices. Two-part tariffs provide a minimal social surplus improvement over Ramsey prices in those cases. When capacity constraints bind, linear pricing can be close to efficient and could achieve nearly all of the social surplus benefits of two-part tariffs pricing.

8 Conclusion

Standard microeconomic models would suggest increasing the number of competitors in the EV fast charging market would drive down prices, but prices have remained high as stations have entered. I show that this is because consumers and stations do not respond to the entry of new stations operated by competing networks. I estimate that quantities decrease at incumbents following own-network entry. Drivers only respond to new stations from the network whose stations they already use, suggesting they do not substitute across networks. I show that this result is not due to differences in charging standards across stations but rather reflects network preferences. There are a number of possible reasons for low cross-network substitution: most networks only post prices in their own mobile application, subscribers may have a subscription to one network, and some some cars came with some amount of free charging at specific networks, which could lead to inelastic demand.

Given the lack of price competition and prevailing high markups above marginal operating costs, I investigate how far prices are from surplus maximizing prices. I estimate a model of demand to recover own- and cross-price elasticities. I find own-price elasticities ranging from -0.99 to -1.78 across networks and times of day, consistent with the -1 to -1.45 Bernard et al. (2025) estimate. I embed the elasticities into a welfare maximization problem to determine the sets of profit maximizing, surplus maximizing, and Ramsey prices.

Observed prices are very similar to the set of linear prices that would maximize profits. There is no evidence that networks are using a two-part tariff system or vertical integration to maximize profits. The choice to use linear prices creates deadweight loss, but I show that at low fixed costs, the deadweight loss is minimal because the most efficient linear prices and two-part tariff prices nearly coincide. This is because capacity constraints push efficient prices above marginal operating costs to ensure markets clear. As fixed costs increase, the

deadweight loss from use of linear prices increases. I estimate that switching to Ramsey prices would increase social surplus by 8-10% depending on the level of fixed costs.

The paper's title asks what is driving high EV fast charging prices? The quantity-weighted average markup above marginal operating cost is 109%. A 48% markup is needed to clear markets and eliminate deadweight loss from misallocation. Beyond that, recovering fixed costs with linear prices requires a 51-84% markup depending on the fixed cost assumptions. Capacity constraints and fixed-cost recovery only explain about one third and one to two thirds of observed markups, respectively. The answer then appears to be that a lack of competition due to rigid consumer preferences is driving high markups.

The most common policy tool to address high prices is increasing competition. However, the entry analysis revealed that market entry does not increase competition between stations. Focusing on the lack of substitution may provide a direction for policy makers worried about high prices. It is possible that the high search costs for finding stations and prices may deter substitution. Regulation that requires stations to make prices accessible through an API so that third-party applications can post prices for all stations could increase competition. Any policies that successfully lower prices could lead to decreased station entry, although reducing search costs could also reduce barriers to entry for smaller networks.

My results suggest that a large share of markups are efficient due to insufficient capacity during peak demand periods. Policy focusing on fast charging should not only address prices but also the net supply of charging. Governments may want to offset potential losses due to pro-competition policies driving down prices by providing larger entry subsidies. Incentivizing more utilization of charging stations during off-peak hours is also a promising option. Increasing data sharing requirements could reduce search costs, which might increase cross-station and cross-hour substitution, potentially reducing the need for more chargers and increasing station surplus, thus reducing the need for subsidies.

Data on the fast charging market is sparse. In this paper, I am able to delve into prices in the fast charging market due to a large data collection effort. However, more data is needed on the costs that stations face and the decisions consumers make to understand the value of government investment in fast charging infrastructure and assess charging station policies. For example, consumer choice data would allow researchers to develop demand models that paint a more complete picture of how drivers substitute between charging locations. Given that low substitution is driving the need for more fast charging infrastructure due to capacity constraints at peak-demand hours, this research could be highly impactful. Partnerships with charging networks or government agencies providing subsidies could be promising for future research on consumer behavior in the fast charging market.

References

AFDC. 2023. "Charging Infrastructure Operation and Maintenance." Department of Energy.

Anderson, Simon P., and Andre de Palma. 1992. "The Logit as a Model of Product Differentiation." *Oxford Economic Papers*, 44(1): 51–67.

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.

Bailey, Megan R., David P. Brown, Blake Shaffer, and Frank A. Wolak. 2025. "Show Me the Money! A Field Experiment on Electric Vehicle Charge Timing." *American Economic Journal: Economic Policy*, 17(2): 259–84.

Baker, Andrew C., David F. Larcker, and Charles C.Y. Wang. 2022. "How much should we trust staggered difference-in-differences estimates?" *Journal of Financial Economics*, 144(2): 370–395.

Baumol, William J., and David F. Bradford. 1970. "Optimal Departures From Marginal Cost Pricing." *The American Economic Review*, 60(3): 265–283.

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.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. "Automobile Prices in Market Equilibrium." *Econometrica*, 63(4): 841–890.

Berry, Steven T. 1994. "Estimating Discrete-Choice Models of Product Differentiation." *The RAND Journal of Economics*, 25(2): 242–262.

Boiteux, Marcel. 1956. "Sur la gestion des Monopoles Publics astreints a l'equilibre budgetaire." *Econometrica*, 24(1): 22–40.

Boiteux, Marcel. 1960. "Peak-Load Pricing." *The Journal of Business*, 33(2): 157–179.

Borenstein, Severin, and James B. Bushnell. 2022. "Do Two Electricity Pricing Wrongs Make a Right? Cost Recovery, Externalities, and Efficiency." *American Economic Journal: Economic Policy*, 14(4): 80–110.

Brent, Richard P. 1973. *Algorithms for Minimization without Derivatives.* Englewood Cliffs, NJ:Prentice-Hall.

Callaway, Brantly, and Pedro H.C. Sant'Anna. 2021. "Difference-in-Differences with multiple time periods." *Journal of Econometrics*, 225(2): 200–230. Themed Issue: Treatment Effect 1.

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

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.

Conlon, Christopher, and Jeff Gortmaker. 2020. "Best practices for differentiated products demand estimation with PyBLP." *The RAND Journal of Economics*, 51(4): 1108–1161.

Conlon, Christopher T., and Julie Holland Mortimer. 2013. "Demand Estimation under Incomplete Product Availability." *American Economic Journal: Microeconomics*, 5(4): 1–30.

Crew, Michael A, Chitru S Fernando, and Paul R Kleindorfer. 1995. "The Theory of Peak-Load Pricing: A Survey." *Journal of Regulatory Economics*, 8(3): 215–248.

Davis, Adam, Tiffany Hoang, Thanh Lopez, Jeffrey Lu, Taylor Nguyen, Bob Nolty, Larry Rillera, Dustin Schell, and Micah Wofford. 2024. "Assembly Bill 2127 Second Electric Vehicle Charging Infrastructure Assessment." California Energy Commission.

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.

de Chaisemartin, Clément, and Xavier D'Haultfœuille. 2020. "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects." *American Economic Review*, 110(9): 2964–96.

Feldstein, Martin S. 1972. "Distributional Equity and the Optimal Structure of Public Prices." *The American Economic Review*, 62(1/2): 32–36.

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.

Gandhi, Amit, and Jean-François Houde. 2020. "Measuring Substitution Patterns in Differentiated-Products Industries." National Bureau of Economic Research Working Paper 26375.

Gardner, John. 2021. "Two-stage differences in differences."

Garg, Teevrat, Ryan Hanna, Jeffrey Myers, Sebastian Tebbe, and David G. Victor. 2026. "Electric vehicle charging at the workplace: Experimental evidence on incentives and environmental nudges." *Journal of Environmental Economics and Management*, 139: 103383.

Goodman-Bacon, Andrew. 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics*, 225(2): 254–277. Themed Issue: Treatment Effect 1.

Hendel, Igal. 1999. "Estimating Multiple-Discrete Choice Models: An Application to Computerization Returns." *The Review of Economic Studies*, 66(2): 423–446.

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.

Littlechild, Stephen C. 1975. "Two-Park Tariffs and Consumption Externalities." *Bell Journal of Economics*, 6(2): 661–670.

McDonald, Loren. 2024. "NEVI DC Fast Charging Station Average Project Cost: $915,000." Paren.

Miyatra, Sukhdev. 2025. "Tesla Reveals V4 Supercharger Costs $40K–$45K Per Unit in North America." Inspire2Rise.

Nevo, Aviv. 2001. "Measuring Market Power in the Ready-to-Eat Cereal Industry." *Econometrica*, 69(2): 307–342.

Oi, Walter Y. 1971. "A Disneyland Dilemma: Two-Part Tariffs for a Mickey Mouse Monopoly." *The Quarterly Journal of Economics*, 85(1): 77–96.

Paris, Francesca. 2025. "How Much It Costs to Drive an E.V. and a Gas Car in Every State." *The New York Times*.

Perloff, Jeffrey M., and Steven C. Salop. 1985. "Equilibrium with Product Differentiation." *The Review of Economic Studies*, 52(1): 107–120.

Ramsey, F. P. 1927. "A Contribution to the Theory of Taxation." *The Economic Journal*, 37(145): 47–61.

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

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.

Sun, Liyang, and Sarah Abraham. 2021. "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects." *Journal of Econometrics*, 225(2): 175–199. Themed Issue: Treatment Effect 1.

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

Tirole, Jean. 1988. *The theory of industrial organization.* Cambridge, Massachusetts:The MIT Press.

Viscusi, W. Kip, Joseph E. Harrington, and David Edward Michael Sappington. 2018. *Economics of regulation and antitrust / W. Kip Viscusi, Joseph E. Harrington, Jr., David E.M. Sappington.* . Fifth edition. ed., Cambridge, Massachusetts:The MIT Press.

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.

APPENDIX

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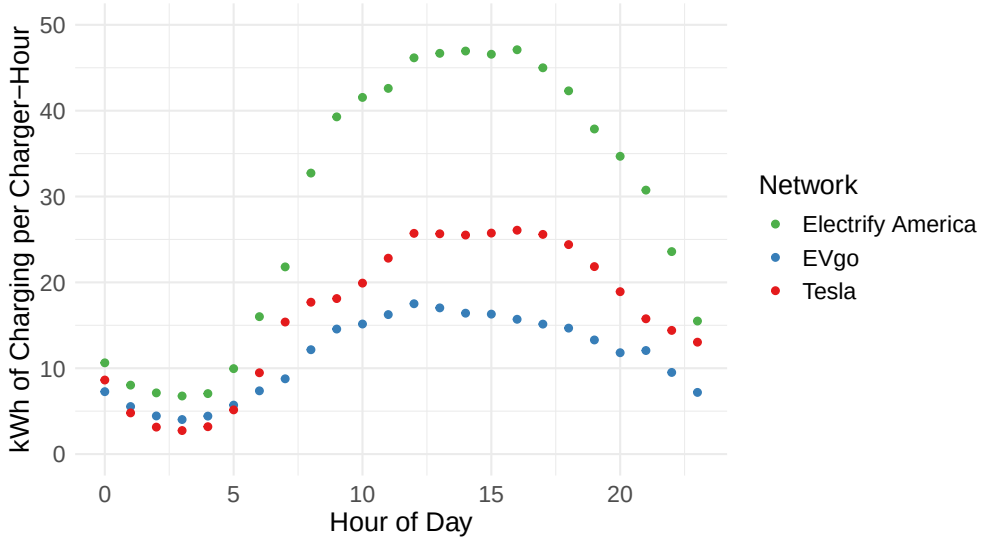
C.2 Solving the Modified Ramsey Problem 60

A Results Appendix

Table A.1: Charging Levels

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 - 60 min.	180-240 miles	Public

Notes: Source: U.S. Department of Transportation.
Charge time is calculated assuming the user charges a 60-kWh battery from 20-80% capacity. Most of the EV models popular in the U.S. have battery capacities around 60-80 kWh.



Notes: Data is for October 2025. Electricity utilization per charger is calaculated at each station and averaged across all stations operated by each network that are served by PG&E.

Figure A.1: Average Hourly Electricity Use per Charger at DCFC Stations Served by PG&E

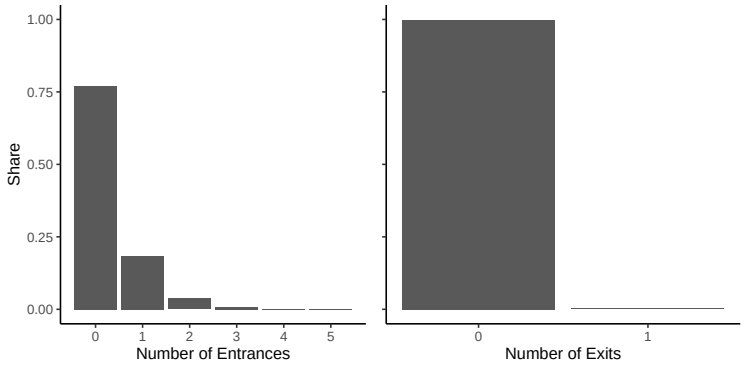
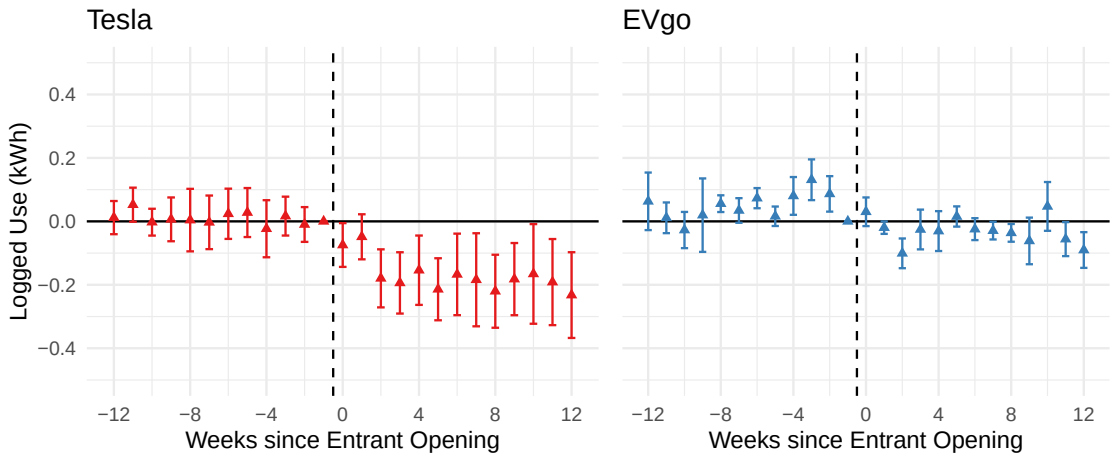


Figure A.2: Frequency of Number of Entries and Exits Experienced by Incumbents

Table A.2: Difference-in-Differences Results

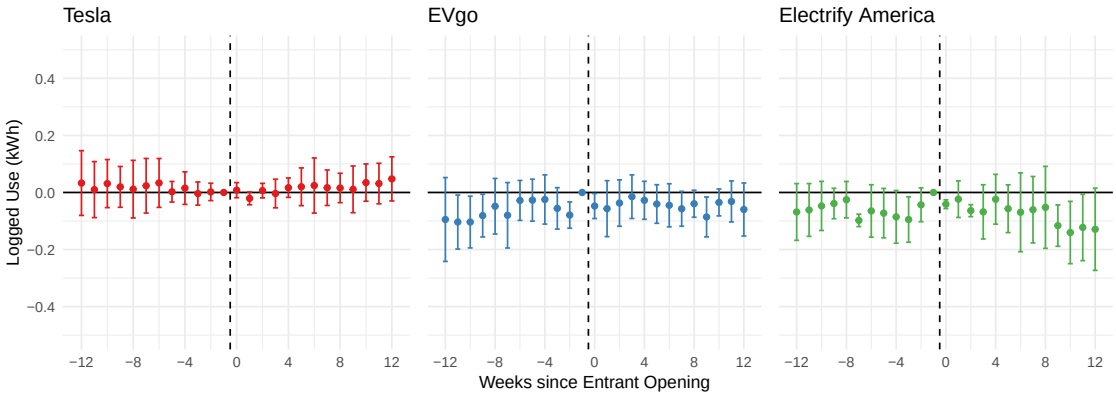
	All		Tesla		EVgo		Electrify America
	Competitor	Own	Competitor	Own	Competitor	Own	Competitor
Log Use (kWh/hour)							
Estimate	0.000	-0.143**	0.001	-0.179**	0.014	-0.073*	-0.014
	(0.014)	(0.019)	(0.017)	(0.028)	(0.025)	(0.013)	(0.036)
Baseline mean	4.557	4.652	5.371	5.457	3.624	3.274	4.294
Observations	1,309,200	335,400	478,200	147,000	420,600	117,000	367,200
Price ($/kWh)							
Estimate	-0.002	-0.002	-0.002	-0.005*	-0.001	0.006**	-0.001
	(0.001)	(0.002)	(0.004)	(0.002)	(0.001)	(0.001)	(0.003)
Baseline mean	0.554	0.468	0.415	0.424	0.604	0.590	0.612
Observations	5,108,616	2,007,072	1,512,216	745,056	2,371,512	854,928	1,224,888
Health Index							
Estimate	-0.463	0.948					
	(1.553)	(0.959)					
Baseline mean	88.6	93.1					
Observations	2,998,560	848,208					
Share Hours with Constrained Capacity							
Estimate	-0.004	-0.046**	-0.007	-0.061**	-0.002	-0.013	-0.001
	(0.007)	(0.008)	(0.008)	(0.005)	(0.003)	(0.004)	(0.008)
Baseline mean	0.079	0.109	0.096	0.126	0.052	0.073	0.080
Observations	1,309,200	335,400	478,200	147,000	420,600	117,000	367,200

Notes: $*/**$ Denote significance at $p < 0.05/0.01$ level.



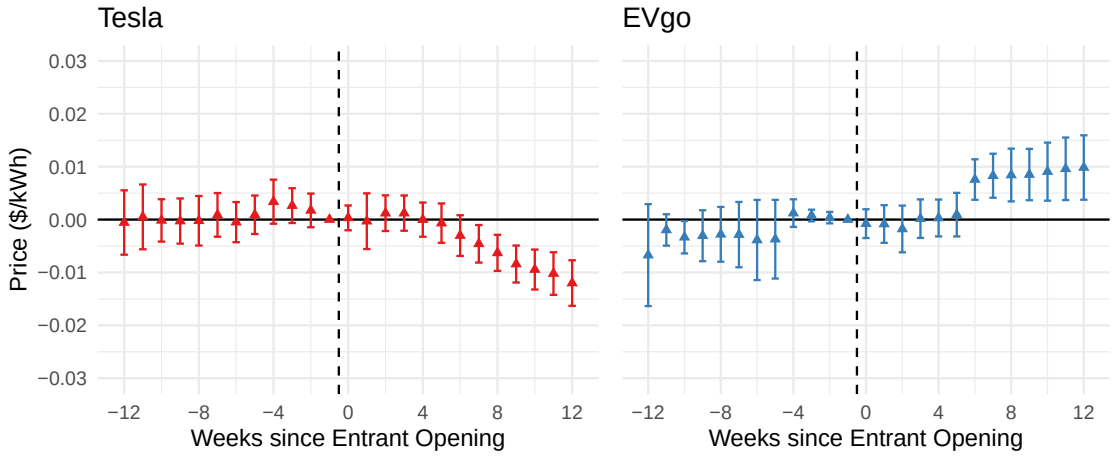
Notes: Data are total electricity consumption at each station and span January 2022 - December 2025. Nearby entry is limited to stations within five minutes of an entrant. Electrify America does not open enough stations near other Electrify America stations to estimate an effect for the network.

Figure A.3: Event Study Estimates of Own-Network Station Entry on Incumbent Hourly Electricity Consumption, by Network



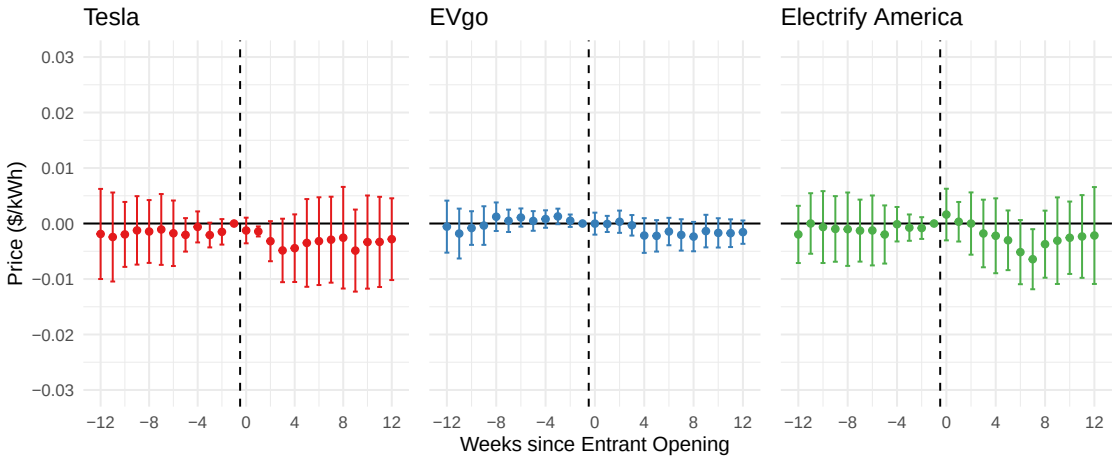
Notes: Data are total electricity consumption at each station and span January 2022 - December 2025. Nearby entry is limited to stations within five minutes of an entrant.

Figure A.4: Event Study Estimates of Competitor Station Entry on Incumbent Hourly Electricity Consumption, by Network



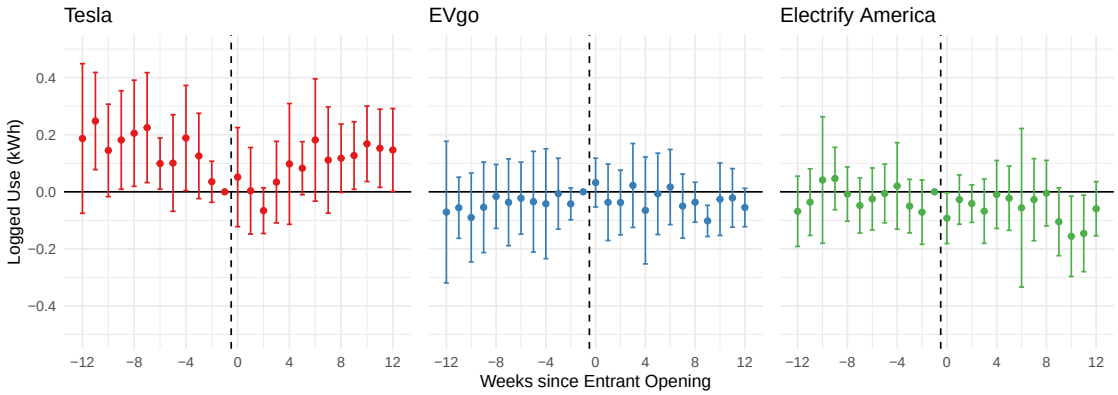
Notes: Data are station-week-hour prices and span October 2024 - May 2026. Nearby entry is limited to stations within five minutes of an entrant. Electrify America does not open enough stations near other Electrify America stations to estimate an effect for the network.

Figure A.5: Event Study Estimates of Own-Network Station Entry on Incumbent Hourly Prices, by Network



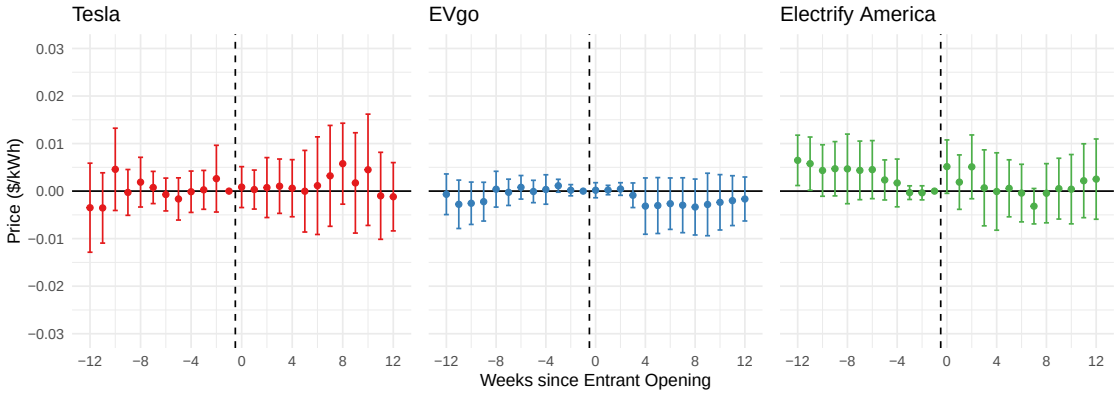
Notes: Data are station-week-hour prices and span October 2024 - May 2026. Nearby entry is limited to stations within five minutes of an entrant.

Figure A.6: Event Study Estimates of Competitor Station Entry on Incumbent Hourly Prices, by Network



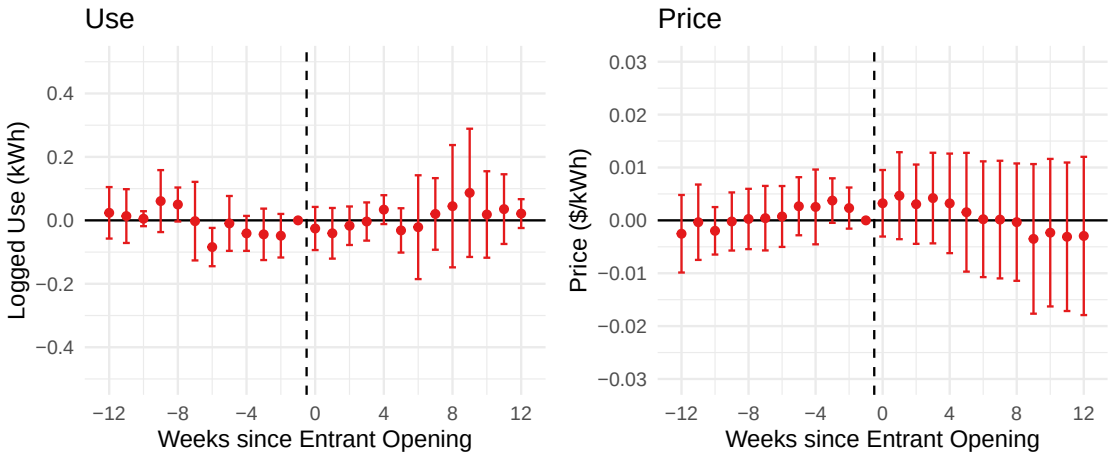
Notes: Data are total electricity consumption at each station and span January 2022 - December 2025. Nearby entry is limited to stations within five minutes of an entrant.

Figure A.7: Event Study Estimates of Entry of Competing Station with Same Charging Standard within Five Minutes on Hourly Electricity Consumption, by Network



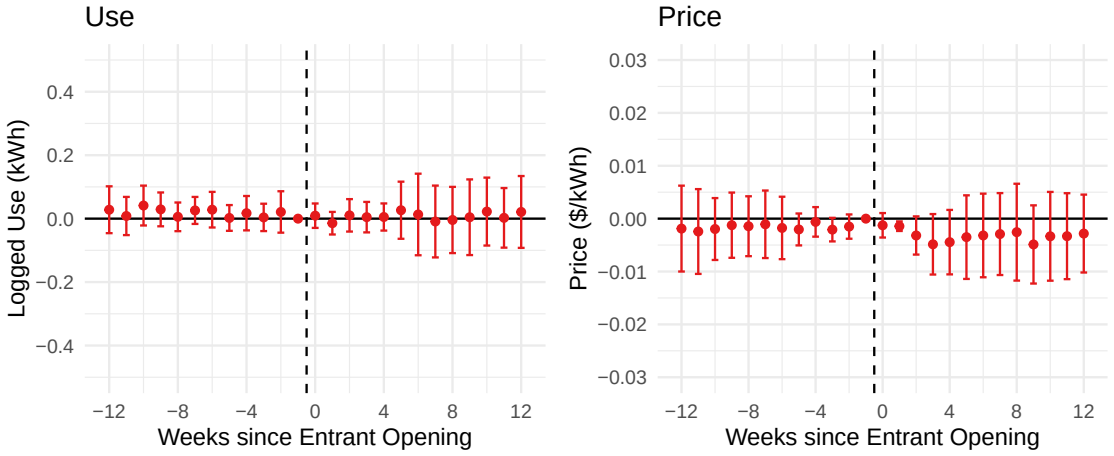
Notes: Data are station-week-hour prices and span October 2024 - May 2026. Nearby entry is limited to stations within five minutes of an entrant.

Figure A.8: Event Study Estimates of Entry of Competing Station with Same Charging Standard within Five Minutes on Hourly Prices, by Network



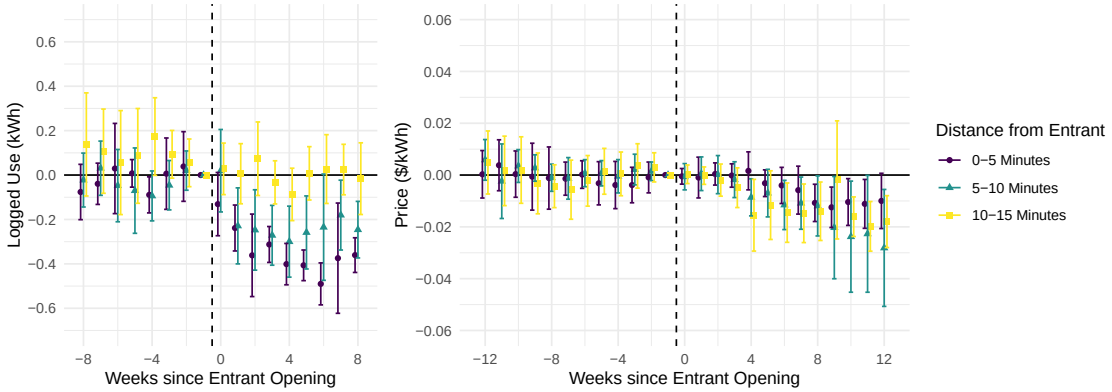
Notes: Data are station-week-hour electricity consumed for charging and prices at each station and span January - December 2025 and January 2025 - May 2026, respectively. Nearby entry is limited to stations within five minutes of an entrant.

Figure A.9: Event Study Estimates of Charging Use and Price at Tesla Stations of Station Adding NACS Chargers



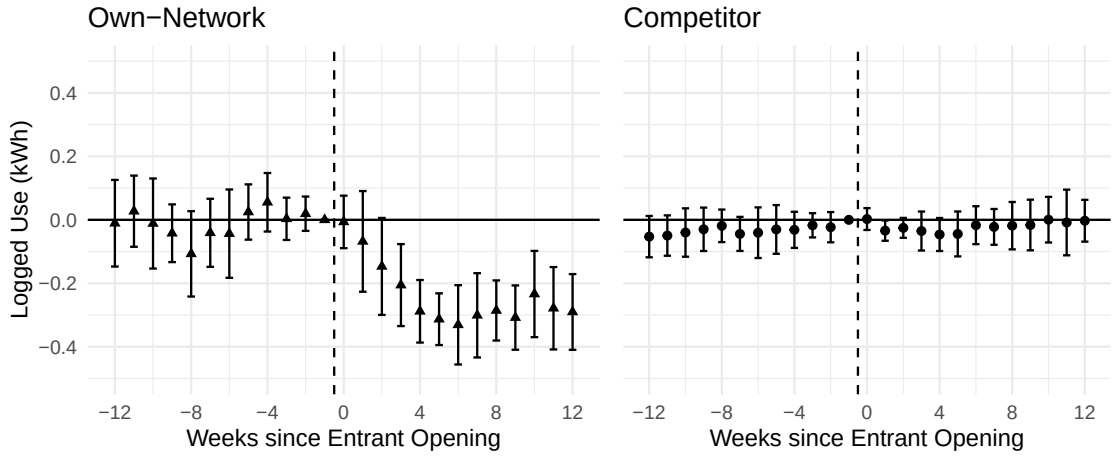
Notes: Data are station-week-hour electricity consumed for charging and prices at each station and span January - December 2025 and January 2025 - May 2026, respectively. Nearby entry is limited to stations within five minutes of an entrant.

Figure A.10: Event Study Estimates of Charging Use and Price at Tesla Stations of Entrant in 2025 or Later



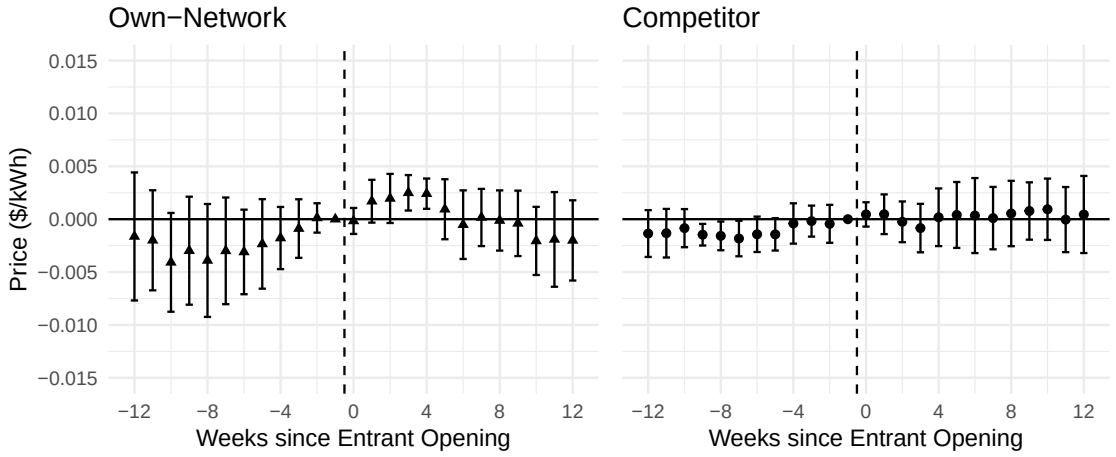
Notes: Data are station-week-hour electricity consumed for charging and prices at each station and span January - December 2025 and January 2025 - May 2026, respectively. Nearby entry is limited to stations within five minutes of an entrant.

Figure A.11: Event Study Estimates of Tesla Own Station Entry within Five Minutes on Incumbent Hourly Electricity Consumption and Price by Distance



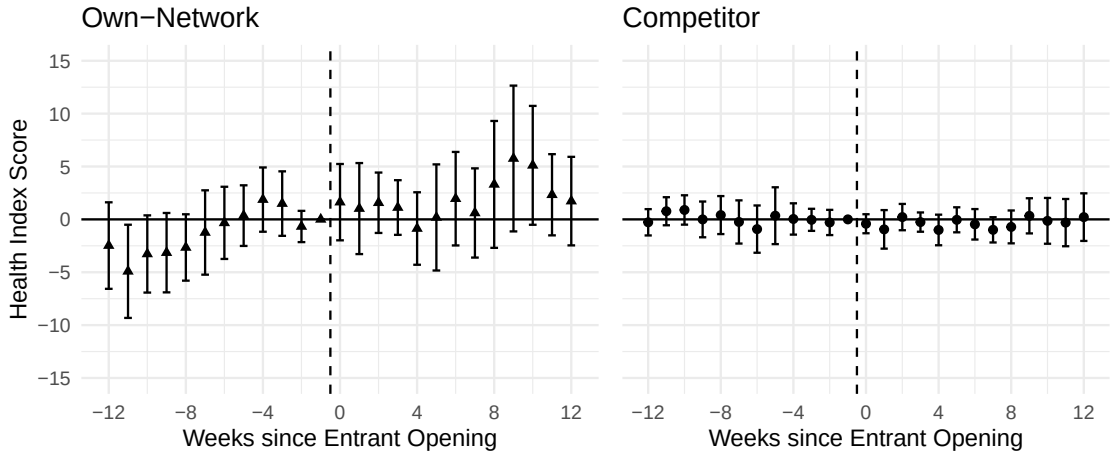
Notes: Data are station-week-hour electricity consumed for charging at each station and span January 2022 - December 2025.

Figure A.12: Event Study Estimates of Own-Network Station Entry within Ten Minutes on Incumbent Hourly Electricity Consumption



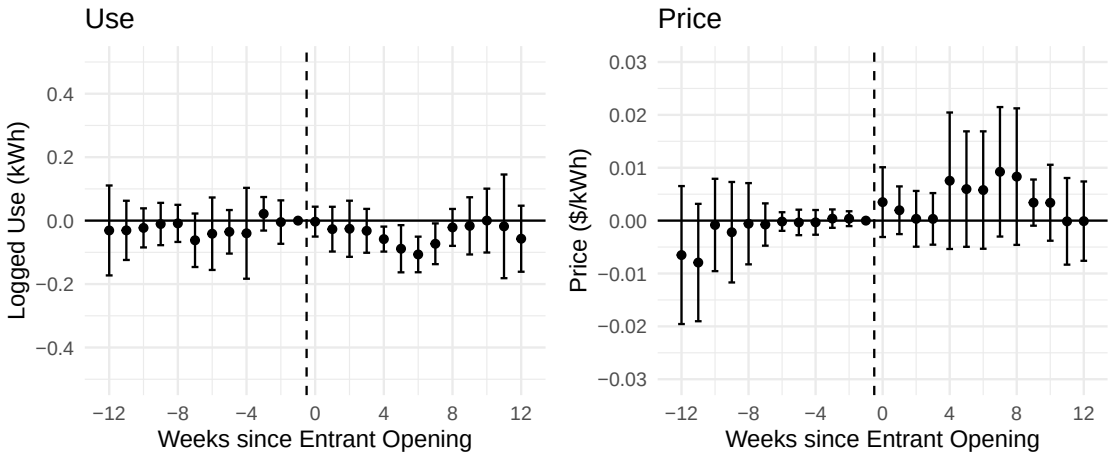
Notes: Data is for station-week-hour prices and span October 2024 - May 2026.

Figure A.13: Event Study Estimates of Own-Network Station Entry within Ten Minutes on Incumbent Price



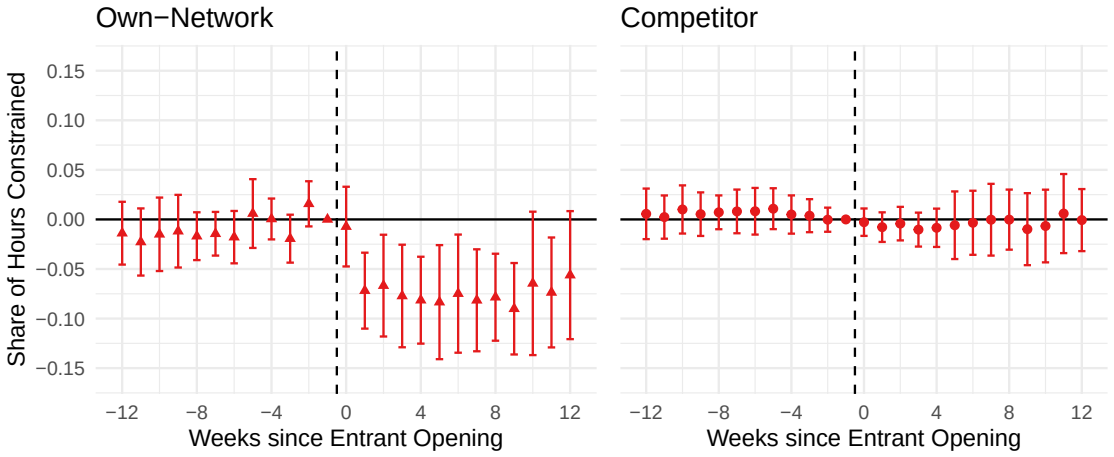
Notes: Data is for station-week health index score and span October 2024 - May 2026. Health Index Score is measured out of 100.

Figure A.14: Event Study Estimates of Station Entry within Ten Minutes on Station Quality



Notes: Data is for station-week-hour electricity consumed and price for charging at each station and span January 2022 - December 2025 and October 2024 - May 2026, respectively.

Figure A.15: Event Study Estimates of Entry of Competing Station with Same Charging Standard within Ten Minutes



Notes: Data is for total hourly electricity consumption at each station and span January 2022 - December 2025.

Figure A.16: Event Study Estimates of Station Entry within Ten Minutes of Tesla Station on Share of Hours near Charging Capacity

Table A.3: Own-Price Elasticity Estimates and Confidence Intervals

Network	Time	Central Estimate	Confidence Interval
All	All	-1.334	(-0.660, -1.886)
EVgo	Morning	-1.527	(-0.722, -2.087)
EVgo	Late Morning	-1.592	(-0.749, -2.152)
EVgo	Afternoon	-1.709	(-0.830, -2.356)
EVgo	Early Evening	-1.780	(-0.852, -2.421)
EVgo	Evening	-1.662	(-0.806, -2.300)
EVgo	Overnight	-1.368	(-0.700, -1.991)
Electrify America	Morning	-1.608	(-0.748, -2.134)
Electrify America	Late Morning	-1.606	(-0.750, -2.134)
Electrify America	Afternoon	-1.604	(-0.767, -2.191)
Electrify America	Early Evening	-1.605	(-0.751, -2.138)
Electrify America	Evening	-1.607	(-0.770, -2.186)
Electrify America	Overnight	-1.601	(-0.801, -2.315)
Tesla	Morning	-1.055	(-0.523, -1.500)
Tesla	Late Morning	-1.169	(-0.580, -1.665)
Tesla	Afternoon	-1.182	(-0.594, -1.704)
Tesla	Early Evening	-1.184	(-0.591, -1.693)
Tesla	Evening	-1.144	(-0.576, -1.644)
Tesla	Overnight	-0.989	(-0.507, -1.455)

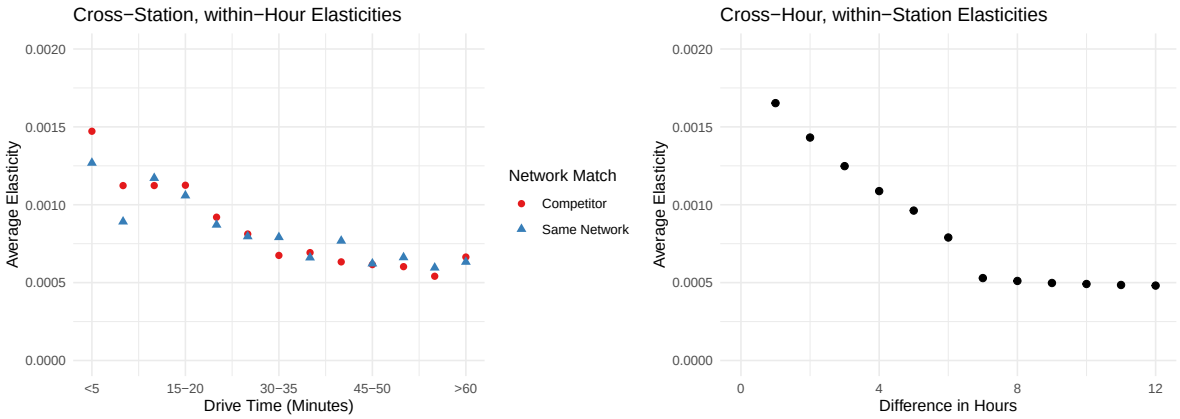
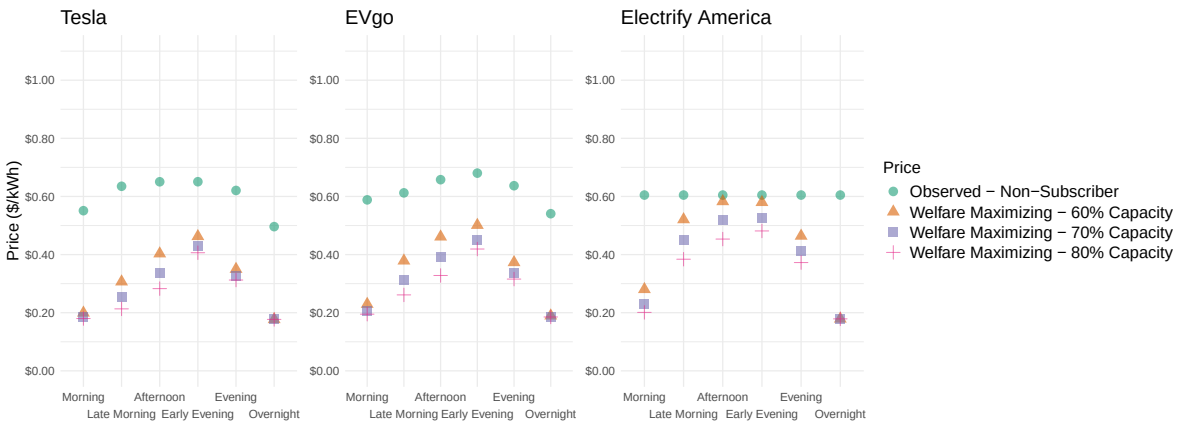


Figure A.17: Cross-Station and Cross-Hour Price Elasticities

Notes: In the left panel, cross-price elasticities are the average cross-station, within-hour price elasticties averaged within five-minute geographic distance bins. In the right panel, cross-price elasticities are the average cross-hour, within-station price elasticities averaged within each hour difference in charging times. Cross-station, cross-hour prices are not depicted in this figure.



Notes: Capacity percentage is how the the percentage of maximum feasible charging used to define capacity. Setting capacity at 60% of maximum feasible charging makes the capacity constraight bind at lower quantities than setting capacity at 70 or 80%.

Figure A.18: Welfare Maximizing Prices under Alternative Capacity Constraints

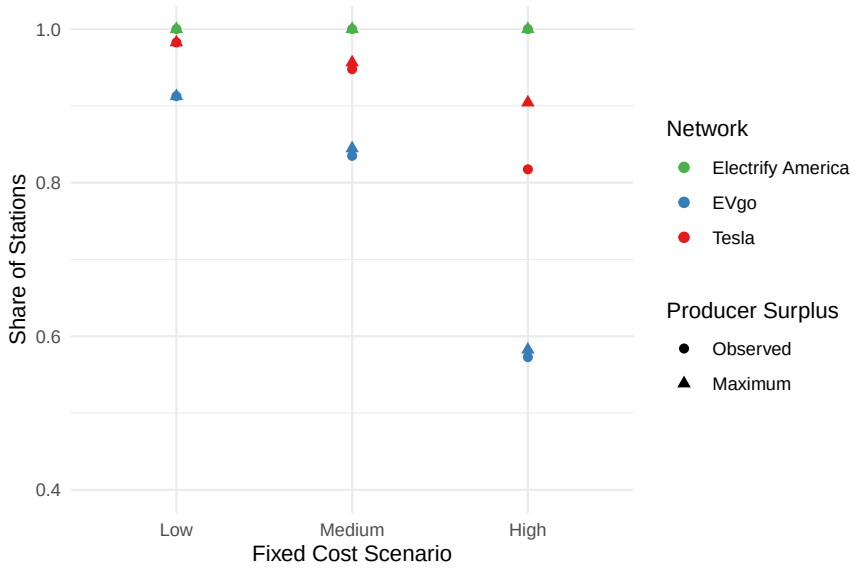


Figure A.19: Share of Stations Able to Recover Fixed Costs

B Data Appendix

B.1 Price Data

Each week, a team of research assistants and I collected hourly prices for all Tesla, EVgo, and Electrify America DCFC stations in California. Data comes from each company's mobile application (Figure B.1 provides a visual of how prices look in the applications) and PlugShare, a third party aggregator of charging station data, which posts EVgo prices. Each of these sources lists prices for each hour during the given day, which allowed collectors to pull all prices for a station at once.

The list of stations comes from querying the Alternative Fueling Station Location API from the DOE's Alternative Fuels Data Center (AFDC) each Saturday. Each data collector would check the hourly prices for a station from the list and enter all 24 prices into a spreadsheet for that week. Data collectors would repeat this process for all stations each week.

The collection period ran from Saturday to Friday each week. Each Saturday I would collect the list of stations from the AFDC, add them to a spreadsheet, and send out a list of collection assignments. Research asssitants were told the deadline for data collection was Thursday, and were in charge of collecting prices for around 100 stations between Sunday and Thursday (there were usually four students collecting EVgo prices and six students collecting Tesla prices, and I collected all Electrify America prices). Friday acted as a buffer day to allow me to collect any missing data and spot check the collected data.

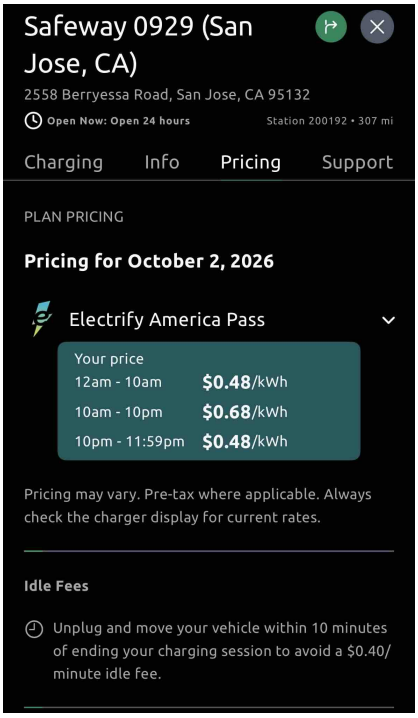
I piloted the data collection process from July through September of 2024 by collecting prices for Southern California stations. This helped create processes for checking data veracity. The data collection spreadsheet included a mechanism to compare against the prior week's prices to make error identification easier. However, there are likely still errors in the data. I compared my data against data from Paren for September of 2025 and found a greater than 99% match rate across all station-hours during the month, which suggests errors were very infrequent.

I have good coverage of stations – the data include prices for 1407 out of 1414 Electrify America, EVgo, and Tesla stations listed in the AFDC data at any point between October 2024 and May 2026. I do not have data on the other seven stations because they did not list prices on their network's application. This most likely means that the AFDC list includes some stations that are not operational and not that networks did not post prices for all stations. My final dataset cover 657 Tesla, 454 EVgo, and 296 Electrify America stations from October 2024 through May 2026, amounting to 2.6 million station-week-hour prices.[38]

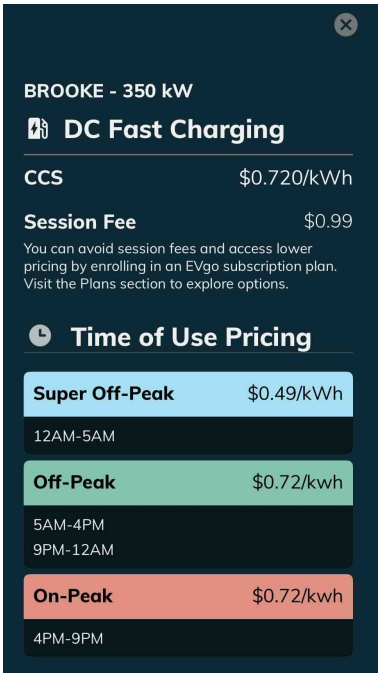
[38]We also collected prices for an additional 52 one-charger EVgo locations that I do not include in this

Prices could be collected any day between Saturday and Friday, and data collectors did not all choose to collect prices the same day. Therefore, it is important to be clear on interpretation of a week's prices as point in time prices collected during that week. My recorded weekly prices at a station will not capture price changes that occured that week if the changes occurred after data was collected. Further, it is possible that during a week where a network changed many stations' prices, some data collectors recorded new prices while some recorded old prices.

Panel A: Electrify America



Panel B: EVgo



Panel C: Tesla

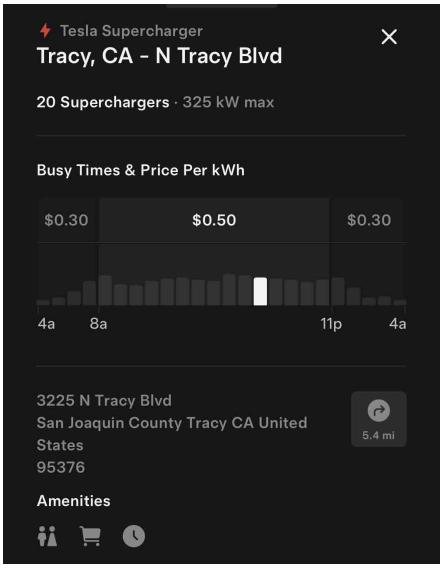


Figure B.1: Price Presentation in Mobile Applications

B.2 Utility Data

Pacific Gas & Electric Company (PG&E) provided metered electricity use data for this project. They compiled all data for meters linked to the list of station addresses from the AFDC and all meters flagged in their data as providing public vehicle charging. Limiting to just stations in PG&E's territory, I am able to match 59% of stations from my price data (EVgo, Electrify America, and Tesla) and 43% of stations from the AFDC data (all stations).

analysis because I focus on locations with two or more chargers.

The low match rates reflect both that I cannot identify all stations in the PG&E data and that some stations may not be served by PG&E. It is possible that even stations PG&E serves will not be in the data they share with me because the station's meter is not at the address listed in the AFDC and the meter is not flagged as for a charging station. Because PG&E sent me data for all meters at the addresses of stations and many are located in large shopping developments, I have meters that are not used for stations. PG&E gives a 1-5 score for likelihood the meter is connected to a charging station. I only keep meters when it is clear that a station is the only customer connected to that meter. This means I am not able to identify many smaller stations that share meters with other businesses and some cases where multiple stations share a parking lot.

One additional caveat is that individual accounts may have multiple meters. Many stations have meters replaced at some point during the sample period, so I build a crosswalk of meters to stations. I aggregate meter data to the station level and use the AFDC station identifier to PG&E station identifier to merge price and use data.

I aggregate all data to the meter-hour level because some meters report hourly and some report every fifteen minutes. The electricity use is raw, and PG&E makes corrections to it before sending bills to customers. However, corrected billing volumes are only available aggregated to the billing period, so I use the raw volumes and acknowledge that they may introduce additional noise into the data.

To calculate hourly charging, I subtract out the baseline usage for each station. I calculate baseline hourly usage as the lowest use at a station. If a station has drivers charging for the entire sample period, I would overestimate the baseline, but this is highly unlikely as there is very little use overnight. If a station's lights are on the same meter as the chargers and are only on overnight, I will slightly underestimate the amount of overnight charging. The amount of electricity the lights use should be relatively low compared to the amount needed to charge a car. I also considered using a baseline calculated as the lowest usage during an hour of the day to avoid this problem. The results were similar between the two, and the latter option increased the probability that I set the baseline too high for station-hours that are consistently busy. It is much more likely that a station always has customers at 2 PM than that it always has customers at all hours.

The panel of station-week-hour charging contains 1.5 million observations for 468 stations over 209 weeks. 178 stations are Tesla stations, 128 are EVgo, 90 are Electrify America, and 72 belong to other networks. I am able to match all to price data, but can only include 115 Tesla, 103 EVgo, and 38 Electrify America stations in the demand estimation model. There are two reasons for the large drop in stations for Tesla and Electrify America. First, Electrify America installed batteries at many of its stations and I omit all stations with

batteries installed because batteries are charged in the late morning (when electricity is cheap) and discharged in the late afternoon (when it is expensive), which will bias estimates. Second, I limit the model to just CBSAs with at least one station from each network and at least 10 stations overall. Many Tesla stations are along highways in more rural areas and therefore are not included in the deamnd estimation.

C Technical Appendix

C.1 Proof of Profit Maximizing Price

Consider a consumer that must choose where to charge among n stations indexed by i. The consumer's preference for charging at each station is given by the vector $\boldsymbol{\theta} = (\theta_1, ..., \theta_n)$ where θ_i includes preferences over nearby amenities (such as grocery stores, restaurants, etc.), charging network, charging standard, and travel costs. The vector of prices at each station is $\boldsymbol{p} = (p_1, ..., p_n)$. The consumer chooses to charge at the station that maximizes net surplus $s_i = \theta_i - p_i$ for $i \in 1, ...n$.[39]

For simplicity, let all consumers' preferences for stations be independent and identically distributed $\theta_i \sim U[-1, 1]$. The cumulative distribution function (CDF) is $G(\theta_i) = \frac{\theta_i + 1}{2}$. The probability that a consumer prefers station i to station j is

$$\Pr(s_i \geq s_j) = \Pr(\theta_j \leq \theta_i + p_j - p_i) = G(\theta_i + p_j - p_i) = \frac{\theta_i + p_j - p_i + 1}{2}. \tag{1}$$

Aggregating over L consumers who each charge at the station where they get the greatest surplus yields station i's quantity:

$$Q_i(\boldsymbol{p}) = \Pr(s_i \geq \max_{j \neq i} s_j)L = L \int \Pi_{j \neq i}[G(\theta_i + p_j - p_i)]g(\theta_i)d\theta_i. \tag{2}$$

Let each station face constant marginal cost c. Then its profit function is

$$\pi_i(\boldsymbol{p}) = (p_i - c)Q_i(\boldsymbol{p}) - K = (p_i - c)L \int_{-1}^{1} (\frac{\theta_i + p_j - p_i + 1}{2})^{n-1} \frac{1}{2} d\theta_i - K \tag{3}$$

where K is the station's fixed cost of entering. Holding competitors' prices constant, the profit maximizing price for each station is:

$$p_i = c - \frac{Q_i(\boldsymbol{p})}{\partial Q_i / \partial p_i}. \tag{4}$$

Assuming symmetry yields the Nash-Bertrand equilibrium. All stations charge the same price $p_i = p$ and sell the same quantity $Q_i = L \int_{-1}^{1} (\frac{\theta_i + 1}{2})^{n-1} \frac{1}{2} d\theta_i = \frac{L}{n}$. The slope of the

[39] For simplicity, I have omitted the outside option of not charging at any station. Adding in the outside option sets an additional restriction that $s_i \geq \bar{v}$ for the consumer to choose station i.

demand curve is $\frac{\partial Q_i}{\partial p_i} = -L\int_{-1}^{1}(n-1)(\frac{\theta_i+p-p_i+1}{2})^{n-2}\frac{1}{4}d\theta_i = -\frac{nQ_i}{2} = -\frac{L}{2}$. Plugging into p_i yields the equilibrium profit maximizing price

$$p(n) = c + \frac{L/n}{L/2} = c + \frac{2}{n}. \tag{5}$$

C.2 Solving the Modified Ramsey Problem

The single-station problem in Equation (14) is to choose the vector of prices for each period of the day, $\mathbf{p} = (p_1, \ldots, p_6)$, that maximizes social surplus subject to the profit constraint and six capacity constraints, one for each time-of-day period. This is a nonlinear program that can be solved using the Karush–Kuhn–Tucker (KKT) conditions. With seven constraints there are $2^7 = 128$ candidate solutions depending on which constraints bind sets. The KKT approach requires comparing each candidate solution that does not violate a constraint. For a network operating n stations, this requires evaluating and comparing 2^{6n+1} candidate solutions. Evaluating every candidate is computationally infeasible, so instead I solve the problem using a numerical approximation.

I exploit the fact that, under a local linear approximation to demand, the KKT conditions are linear in prices once the set of binding capacity constraints is fixed. Demand is approximated around the observed prices and quantities as $\mathbf{q}(\mathbf{p}) = \mathbf{q}^0 + \mathbf{B}(\mathbf{p} - \mathbf{p}^0)$, where $B_{ij} = \eta_{ij}\, q_i^0/p_j^0$ and η_{ij} is the PyBLP-estimated elasticity of product i's demand with respect to product j's price. For a given set of capacity-bound products and a given multiplier $\kappa \geq 0$ on the profit constraint, the first-order conditions and the binding capacity constraints form a system of linear equations that I solve exactly.

I first solve with the profit constraint slack ($\kappa = 0$); if profit meets the floor, this is the solution. Otherwise, I use Brent's root-finding method to find the κ at which profit exactly equals the floor (Brent, 1973). The set of capacity-bound products is found with an active-set procedure: starting with none binding, I add products that exceed capacity and release bound products that no longer need to bind, re-solving after each change until no further change is needed. Because each iteration is a single linear solve, the computation grows roughly in proportion to the number of capacity-constrained products. This is much less computationally intensive than solving for 2^{6n+1} candidate solutions.