Entry and Coordination in the U.S. Electric Vehicle Charging Industry

Jing Li Katalin Springel *

September 8, 2023

[PRELIMINARY DRAFT. PLEASE DO NOT CIRCULATE PUBLICLY.]

Abstract

This paper evaluates the efficiency of market location choices for electric vehicle (EV) charging stations. The charging industry is central to electrifying the transportation sector and receives billions of dollars in government support. However, little is known about how the charging industry is organized and how government funds can improve the efficiency of this market. We use novel data about EV charging station utilization in the U.S. to test for the presence of entry complementarities, a form of positive spillovers, across charging locations. We develop a measure of how much firms in the charging industry internalize their positive spillovers on other locations. Our paper provides a micro-foundation for EV charging stations subsidy policies with location targeting or spatial restrictions.

1 Introduction

Climate change is one of the most important and complex challenges facing the world, and the transportation sector is one of the largest contributors to climate-changing greenhouse gases. A transition to a low-carbon transportation sector is a high-priority policy objective in many countries. The mass adoption of electric vehicles (EVs) remains a promising path for dramatically reducing greenhouse gas emissions from the transportation sector. The electric share of new vehicle sales relative to conventional gasoline vehicles is growing rapidly. The growth of the EV market depends on consumer valuation of features of EVs and non-EVs, including purchase price, fuel costs, refueling time, vehicle acceleration, and, importantly, charging infrastructure.

*Li: MIT Sloan School of Management, lijing@mit.edu. Springel: HEC Montréal, katalin.springel@hec.ca. We thank Shanjun Li, James Stock, and Xibo Wan for helpful discussions and suggestions. This work was generously supported by grants from the MIT Future Energy Systems Center and the MIT Sloan Junior Faculty Research Assistance Program.

The availability of refueling infrastructure is crucial for any alternative fuel transportation technology to successfully compete against incumbent gasoline. However, in the EV market, the charging infrastructure industry is still heavily supported by subsidies from government. The International Energy Agency estimates that investment in public EV charging infrastructure increased by more than 20% in 2021 and is expected to reach $10 billion in 2022 (International Energy Agency, 2022). Furthermore, in the US, the 2021 Infrastructure Investment and Jobs Act directs $7.5 billion toward EV charging infrastructure, and a subsequent memo clarifies that $5 billion will be devoted to building fast charging stations at most 50 miles apart along U.S. highways. Governments around the world have established similar measures and policies, recognizing the essential role charging infrastructure plays in spurring EV adoption. In addition to generous support from governments, the EV charging industry greatly relies on support from the automobile manufacturers. This contrasts with the gasoline transportation system, where the firms that produce vehicles are separate from the firms that produce and distribute the fuel for those vehicles. The accelerated rollout of EV charging stations is crucial to a variety of decision makers, yet the issue remains largely understudied – providing a unique opportunity for this research project to address unresolved questions in the economics literature and inform current and future policy debates. While this research project focuses on EVs and refueling systems for EVs, the modeling framework developed in this project and the insights learned about the EV market can contribute to the wider understanding of how to support the growth of other alternative fuel transportation systems.

For these reasons, it is critical to understand how government subsidies aiming to support the EV infrastructure can be efficiently allocated and how the EV charging industry – the provider of 'fuel' for EVs – can become profitable earlier and outgrow reliance on subsidies from government and automobile manufacturers. Prior work (see for example Li et al. (2017) and Springel (2021)) has studied the indirect network effects in this two-sided market and found that supporting charging infrastructure would spur EV demand. Prior work gives little guidance about the efficacy of differentiated subsidies, such as based on station location, charging speed or other characteristics, while many observed policies and subsidies restrict eligibility by station characteristics. For example, the U.S. IIJA primarily supports fast charging stations located near highways and spaced every 50 miles. European regulation requires charging stations every 60 kilometers offering at least 150kw of power.[1] The efficiency of this type of policy crucially relies on the existence of frictions in where the market locates charging stations, which is a different type of market failure from en-

[1]Council of the EU Press Release, 2023 July 25, Stable URL.

vironmental externalities and a specific form of indirect network effects from two-sided markets. If the market generates 'holes' in charging networks, then the every-50-mile subsidy could be efficient. Otherwise, a uniform subsidy over locations would be sufficient to internalize any environmental advantages of electric vehicles. Similarly, to the best of our knowledge, the economics literature has not yet analyzed in detail the business decisions of the EV charging industry such as pricing and coordination of station entry into networks. Therefore, in this project, we seek to answer the following research question: Would it be more efficient for governments to introduce geographically targeted station subsidies instead of uniform subsidies that do not restrict eligibility by location or other station characteristics?

We have compiled a panel dataset of travel patterns, vehicle market outcomes and EV charging industry outcomes in the US from 2011 to the present. In particular, we obtained a sample of 45 million cellphone users' location data to observe travel patterns by distance traveled, time spent and trip purpose. We combine this data with detailed vehicle registration data which includes vehicle identifiers, quantities sold and car attributes. Finally, a key data component to analyzing the EV charging industry and the role of related government incentives, is detailed information on the EV charging network and its evolution over time. In addition to historical data on charging station entry, location, network, connector types and counts, we acquired utilization at finely disaggregated geographic and time levels, as well as charging fees and customer reviews allowing us to map out pricing information and frequency of station visits. Using this uniquely rich data, we are able to analyze entry and coordination decisions of EV charging stations.

In this paper, we first show empirical evidence of complementary spillovers across charging stations. This is necessary step to determine whether government subsidies should be distributed uniformly or focus on highway corridors since the presence of spillover would necessitate targeted policy instruments. We have designed two empirical tests for the presence of entry spillovers. First, we investigate the impact of entry events on incumbent charging station utilization when the entry events occur at different distances away. We hypothesize that when entrants are on the same charging standard as an incumbent (and thus share potential charging customers), entrants may have entry spillovers on incumbents. At close distances, those spillovers may be negative, such as from business-stealing, while at appropriate distances apart, entrants may increase incumbent utilization by enabling trips that EV drivers could not otherwise take. We find that entry 75 to 150 miles away from an incumbent when they share charging standards is associated with a .49 percentage point increase in incumbent utilization demand, or 3.5 hours of more charging in a

month. When entrants and incumbents do not share charging standards, we do not find evidence of any entry spillovers, which helps alleviate concerns that our findings of positive spillovers may be driven by common unobserved demand shocks or expectations.

Our second test of positive spillovers adds more structure through the physical road and highway system. Using the data about opening dates, locations, and our measure of demand at individual EV charging locations, we can test whether the entry of a new charging location leads to an increase in demand at incumbent locations that are on the same routes between major urban population centers. The intuition for this hypothesis is that newly entering charging stations may fill up certain 'holes' in the charging network, making possible EV trips that were not viable or convenient. However, there will also be a business-stealing effect from competitor entry, especially if a newly entering station is built near existing charging locations. Thus, whether demand at an incumbent station increases or decreases after a new station enters depends on the relative magnitudes of these two effects: positive complementary spillovers and negative business-stealing effects. In particular, we link incumbents to entrants by whether they are on the same route between any pair of large cities (Census Urban Areas) in the U.S. When the stations are at most d miles apart, we consider a route connected at d miles. For example, the IIJA implementation plan is to connect routes at 50 miles. We use the connection event of the route in event studies for a range of distances from 30 to 150 miles and analyze each charging standard separately.

We find that Tesla charging stations on a route receive more charging demand (about .5 more visits per station and month, on average) when routes become connected at 70 to 120 miles and do not find effects of connection events at 30 to 50 miles or 150 miles. In contrast, EVs on the Chademo and SAE Combo standards have higher variability in range and include many shorter-range EV models. On the other two charging standards, we find that incumbent charging demand increases when routes become connected at 30 to 50 miles and no discernible effects for longer distances. These findings are consistent with drivers charging at stations spaced appropriately apart for the range of EV that they have. Our results suggest that charging stations are complements for EV drivers when the stations are located appropriate distances apart from each other or in specific spatial configurations. The first condition for spatially targeted charging station subsidies to be efficient, the existence of positive spillovers, is thus satisfied.

Lastly, we are investigate how much of these entry spillovers are already internalized in the entry decisions of charging stations and charging networks. We find substantial heterogeneity in how networks prioritize network contributions and site-specific benefits. A uniform subsidy is

unlikely to efficiently achieve any social planner objective with a focus on spatial allocation of stations.

Our paper contributes to several strands in the economic literature. First and most importantly, a recent literature in economics examines the EV market and government policy focusing on the role of charging networks (Springel, 2021; Li, 2019; Li et al., 2017), energy and emissions (Gillingham et al., 2021; Holland et al., 2022, 2016), and driver behavior (Sinyashin, 2021; Dorsey et al., 2022; Houde, 2012). The contribution of our paper to this growing body of work on EVs is twofold. First, we examine whether subsidies aimed at promoting the expansion of the public charging station network should be targeted based on station attributes. Second, to the best of our knowledge, we are the first to be able to obtain and take advantage of charging station utilization, pricing and customer check-in data.

This analysis also relates to the large body of work studying firm entry that builds on game-theoretic models of static entry first developed by Bresnahan and Reiss (1990, 1991). Recent papers in this literature have added complexities such as endogenizing product-type firm decisions (Mazzeo, 2002; Seim, 2006), relaxing the isolated-markets assumptions (Jia, 2008; Holmes, 2011; Nishida, 2015), and examining the competitive effects of entry (Whinston and Collins, 1992; Goolsbee and Syverson, 2008; Arcidiacono et al., 2020). Our work contributes to this literature by testing for the presence of positive entry spillovers for products (charging stations) at different locations and assessing the social efficiency of the market provision of product locations.

Finally, our work contributes to the broader literature on game theory and assortment planning that studies firm decisions on the choice of product selection. In particular, Cachon and Kök (2007) study how the presence of consumers who purchase merchandise from multiple categories might affect the firm's profit maximization problem and variety choice. They compare a decentralized approach in which the focus is on maximizing profits within each merchandise category to a centralized approach that accounts for interactions between different categories that exist due to the presence of consumers who desire to purchase from various categories. Our paper contributes to this literature by examining whether charging networks should follow a decentralized or centralized approach regarding the expansion of their charging stations.

2 Background and Data

2.1 Background

The electric vehicle (EV) market has grown dramatically since their modern revival. After Tesla first unveiled the Roadster, a high-priced electric sportscar, at an auto show in 2006, Nissan released the LEAF as a more mass-market option in December 2010. Now, nearly every carmaker offers EVs in their product line. EV market shares in the 4th quarter of 2022 in the U.S. reached nearly 6%. Despite the recent dramatic growth in EV market shares, there is a long way to go to reach the stated policy targets of 100% new sales being electric by 2030 or 2035 in the U.S.

Any vehicle that can be recharged by plugging in is called an EV. EVs may be fully electric, called battery-electric vehicles (BEV), or they may include a gasoline engine, which makes them plug-in hybrids (PHEVs). EVs share many characteristics with gasoline vehicles, and consumers who consider EVs may choose based on their priorities for certain characteristics such as power, body style, fuel efficiency. In addition to the characteristics that are common to all cars, buyers of EVs may also pay attention to some characteristics that are particularly important to EVs, such as battery capacity, battery range, and charging network size and location.

The analog of gas stations for gasoline-powered cars is charging stations for EVs. Options for recharging EVs range in speeds. Level 1 charging is with any ordinary electrical outlet and is the slowest option. A full charge at Level 1 may take overnight or even multiple days. Level 2 charging is at a power level similar to a home oven or electric dryer. Residential charging stations, as well as most charging stations offered by employers and retail establishments are Level 2. Level 2 charging takes 4 to 6 hours. The fastest charging speed is called Level 3. Although the slowest Level 3 charging station may be as low as 7kW of power output, the fastest Level 3 charging stations range from 150kW to as much as 450kW. Level 3 stations tend to be sited near highways, where drivers need recharging in a few minutes before getting back on their way.

Three different charging standards for fast (Level 3 or DC) charging are present in the U.S. EV industry: Tesla, Chademo, and Combo. Tesla developed its own charging standard and also produces EVs. Chademo is a charging standard developed by a consortium of automakers primarily from Asia and led by Nissan. Combo is developed by the Society of Automotive Engineers and is short for "SAE J1772 CCS Type 1." Most European and American automakers now use Combo, as well as any carmakers that have switched from Chademo to Combo (such as Kia). Tesla has developed two one-way adapters for their drivers to access the other two networks. The Tesla-

to-Chademo adapter became available in the U.S. market in 2015, and a Tesla-to-Combo adapter became available in 2021. It is currently not possible for EVs on other standards to use Tesla charging stations, though Tesla is running some pilot programs to open up their charging stations to other vehicle brands and standards. We design placebo tests around the existence of incompatible standards. For example, an incumbent of one standard should not be affected by changes on other standards' networks in the short run, before consumers have had time to react in their car purchases.

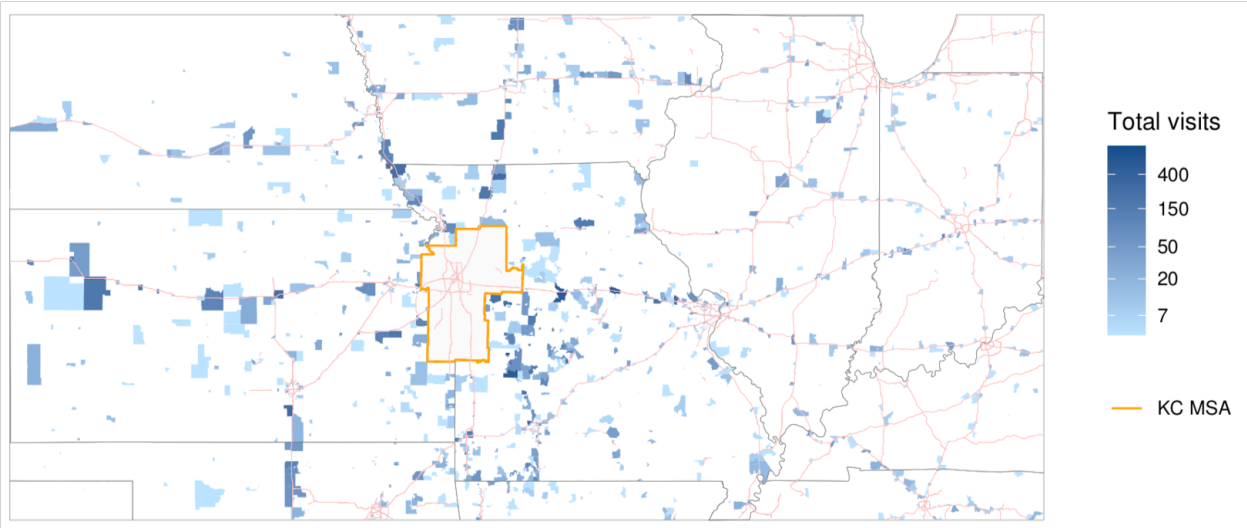
2.2 Data

This paper builds on three main categories of data: travel patterns, vehicle market outcomes, and EV charging industry outcomes.

The data on travel patterns comes from three main sources. First, the National Household Travel Survey (NHTS) provides information on trip distances, purposes, modes, and vehicle portfolios for a representative sample of households in the United States as shown in Tables A1 through A4. However, the NHTS is only statistically representative at the national level and may be too noisy or sparse at more disaggregated levels such as city and county. The second source is county-to-county commuting flows from the American Community Survey (ACS). Both the NHTS and the ACS are publicly available and easily accessible. This research focuses on the importance of availability of charging locations, so we ideally want as disaggregated data as possible. The third source of data on travel patterns is from SafeGraph, which collects location information from a sample of 45 million cellphone users. The cellphone location data have been matched to business addresses, providing us with a distribution of commercial locations visited by users in each census block group. Figure 1 illustrates the SafeGraph Patterns data by showing gas stations visited by people who live in Kansas City, Missouri. Gas stations with more frequent visits have darker shading. The SafeGraph Patterns data track visits to other business types besides gas stations. These data have been shown to be representative of the US population, and only a handful of census block groups are not represented among the users.

Information on vehicle market outcomes include quantities sold of each vehicle model, vehicle characteristics, prices, and buyer demographics. A vehicle model is defined by make, model, model year, fuel type, and trim. We have purchased data from Experian Automotive on the universe of vehicle registration counts in the US by make, model, model year, and trim, at finely disaggregated geographic (census tract) and time (month) levels, from 2013 to 2023. These data on vehicle quantities are very detailed in the vehicle, geography, and time dimensions, which will allow us to

Figure 1: Visits to Gas Stations by People Who Live in KC, MO, Aug 2020; SafeGraph

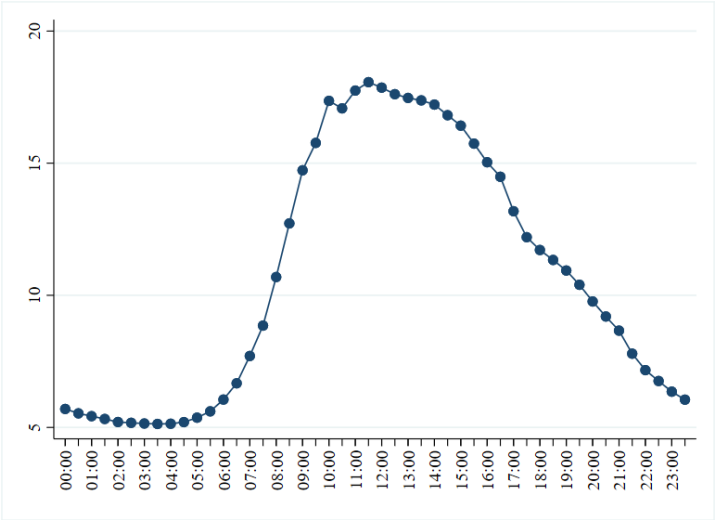


merge flexibly with other datasets. Detailed vehicle characteristics and list price data have been purchased from DataOne, such as engine power, fuel efficiency, number of doors, and manufacturer suggested retail price. We supplement the DataOne characteristics data with publicly available information from the US EPA about EV battery capacity. Transaction-level micro-data for a nationally representative sample of buyers in each year is available from the InMoment (formerly MaritzCX) yearly New Vehicle Customer Survey (NVCS), which we have acquired for the years 2010 to 2020. Each year, InMoment collects survey responses from about 200,000 households who purchased a new vehicle in each year, or 1% of vehicle buyers. The InMoment NVCS allows us to observe transacted price and demographics of the buyer, including household income, age of household head, zip code of residence, and an urbanization indicator.

The third component of our dataset is about charging stations. Data on GPS coordinates defining station location, entry date, connector count and types, network affiliation, and amenities are made publicly available by the U.S. Department of Energy's Alternative Fuels Data Center (AFDC) on a daily basis. Since historical data is not stored by AFDC, we have collected and archived these daily files regularly from 2015 to the present.

Information on EV charging demand is the most critical as well as novel part of our dataset. The most ideal dataset would include the number of charging sessions and kilowatt-hours (kWh) of electricity delivered for each charging station. Instead, we have access to two coarser measures of charging demand. First, we observe charging station utilization from 2015 and 2016 for the entire US and several networks, and then from November 2021 to the present in California for one

Figure 2: Utilization Profile Averaged over Days



Notes: This figure plots the charging profile for one network in California in November 2021. The horizontal axis begins at midnight and increments in half-hours. Each point represents the percentage of stations that are in-use at a given time, averaged over days in November 2021.

of the largest charging networks. The utilization data provides information at 30-minute intervals regarding whether a charging station was in-use, available, or out of service. Figure 2 shows the utilization profile throughout the day for one network in California, averaged over days in November 2021. Our paper focuses on public charging stations. The utilization profile rises beginning in the morning, peaks at mid-day, and falls to the lowest point overnight. Private residential charging stations may show a different charging profile throughout the day.

Second, we have nearly 2 million check-ins and reviews from a crowd-sourced 3rd-party website and app from 2011 to the present. Each check-in contains a user identifier, station identifier, and timestamp, which can be aggregated to a check-in count at each station in each time period as a second measure of charging demand. Some check-ins also include the EV model of the driver, which we use to understand travel distances between charging events. The correlation between our two charging demand measures – utilization and number of check-ins – is .27 for cumulative check-in counts and .22 for new monthly check-in counts. These check-in data also allow us to link check-ins across individual users and examine how users change their visited stations over time in response to network expansion. We have also collected detailed station characteristics that may be relevant to drivers, such as charging fees, nearby amenities, and customer ratings and reviews.

3 Impact of Entry by Distance

We begin by investigating whether a new charging station entrant generates positive spillovers for incumbent charging stations in growing distance bands away from the incumbent. The estimating equation is as follows:

$$y_{jt} = \beta_0 + \sum_d \beta_d \text{Competitors}_{jdt} + \gamma_j + \gamma_t \gamma_{ct} + u_{jt}, \tag{1}$$

where y_{jt} is charging demand at incumbent station j in period t, d denotes distance bands from station j in time period t. Station fixed effects γ_j control for time-invariant station attributes, such as location. Time (month) fixed effects γ_t control for unobservables that are fixed for a given time period, such as seasonality and time-related national trends. City-by-time fixed effects γ_{ct} control for time-varying unobservables at the city level, such as local expected EV demand. The identifying assumption for interpreting β_d as the impact of entry on incumbent j's utilization is that there are no common unobserved demand shocks far away. We plan to develop an instrumental variable using panel variation in EVs on the road arising from EV subsidies.

At what distance rings might we expect to see entry spillovers on incumbent charging demand? The range of an EV is an upper bound on how far a driver can go between recharges. It is an upper bound because EV drivers are generally advised to charge their EVs before completely depleting the battery, but you cannot go beyond the capacity of the car's battery. In fact, dealerships often recommend to EV owners to keep their car's battery between 30% and 80%.

Figure 3: Electric range of EVs that charge at Level 3 stations, 2020-2021

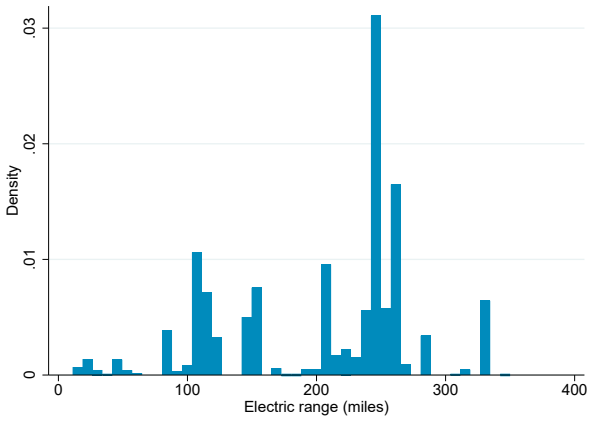
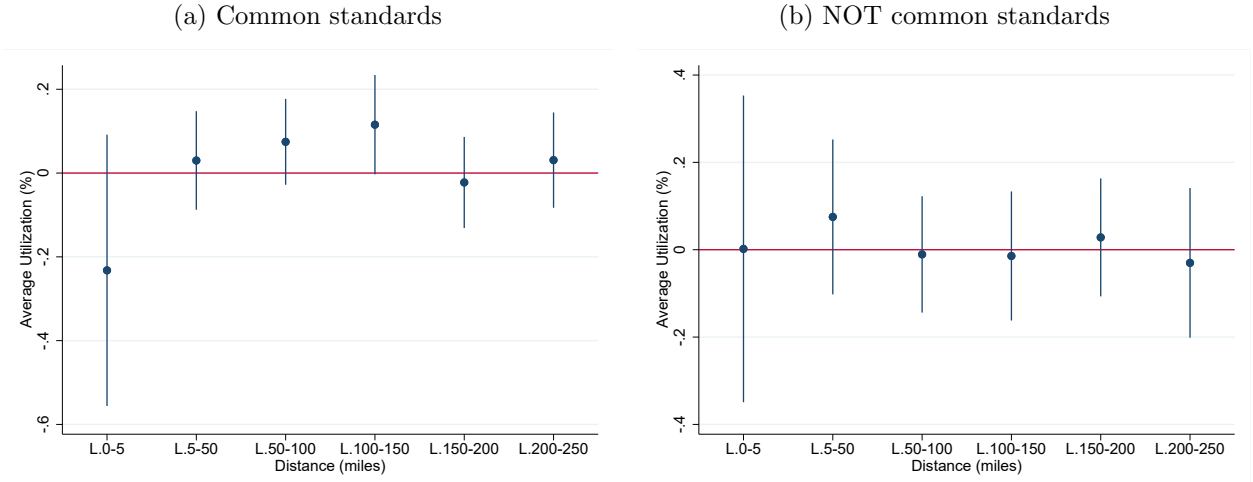


Figure 3 plots a histogram of the electric range of EVs that charge at Level 3 (fast) charging stations in our check-ins dataset. A significant share of cars charging at these stations have electric range of 200 to 275 miles. We define distance bands guided by the empirical distribution of EV

ranges observed at Level 3 charging stations along highways. We estimate Equation 1 using data on charging station utilization from November 2022 to July 2023 in the United States.

Figure 4 presents the estimated impacts of entry on incumbent charging demand by charging standard at different distance bands. Subfigure (a) shows impacts from entrants when they share the same charging standard as the incumbent. At 0 to 5 miles from an incumbent, while the estimates are consistent with business stealing, very little entry occurs, which leads to the large standard error bars on the estimated coefficient. A new charging station between 5 to 150 miles from an incumbent increases incumbent utilization with the effect being larger at larger distances from the incumbent. However, this effect is not statistically significant. One explanation for this finding is that EV drivers might not view charging stations sharing a common standard, but belonging to different networks as perfect substitutes due to the hassle, time, and monetary costs associated with using several different networks. In a placebo test (b), we find no evidence of spillovers when the entrant and incumbent are on different charging standards, which alleviates concerns about common unobserved demand shocks driving both entry and increases in incumbent utilization.

Figure 4: Impact of entrants on charging demand at incumbents by standard



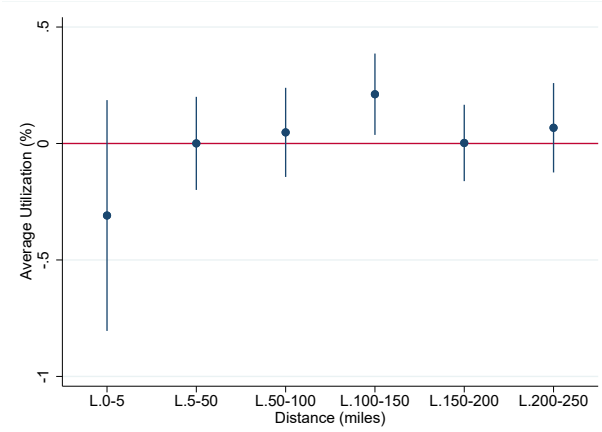
Notes: This figure presents estimated impacts of charging station entry on incumbent charging demand at different distance bands. In (a), entrants are on the same standards as incumbents. In (b), entrants are on different standards as incumbents. The outcome variable is utilization rate measured as the fraction of hours in each month that public charging stations are observed to be in use.

Next, we estimate the spillover effects of entry on incumbent utilization by network affiliation and charging standard at different distances away and the results are shown in Figure 5. Subfigure (a) shows impacts from entrants when they share charging standard and network with the

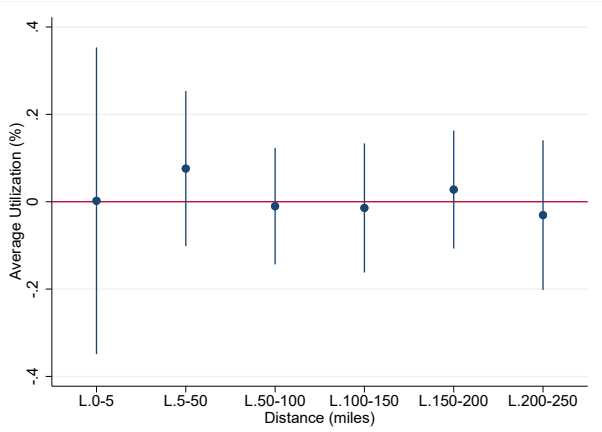
incumbent. Similarly to the previous results, at 0 to 5 miles from an incumbent, the estimates are consistent with business stealing, but there are large standard error bars on the estimated coefficient due to small number of entry occurring so close to incumbent stations. Adding a new charging station between 100 to 150 miles from an incumbent is associated with a .21 p.p. increase in utilization of the incumbent, which translates to 3.31% increase in utilization or 131.1 hours per month. As a robustness check, we also estimated the impact from entrants when they belong to the same network as the incumbent (but do not necessarily share charging standard) and the results remain similar. In a placebo test (b), our findings do not indicate any spillover effects when the new entrant and the established incumbent are affiliated with different networks and do not share a common charging standard. In additional placebo tests, we confirmed that these results do not change even if we include cases where the entrant and the incumbent belong to the same network but have different standards as well as when the entrant and the incumbent are affiliated with different network but share the same standard. These tests further help mitigating concerns that these findings are a result of common unobserved demand shocks.

Figure 5: Impact of entrants on charging demand at incumbents by network affiliation

(a) Common network and common standard



(b) NOT common network, NOT common standard

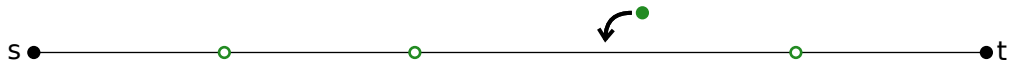


Notes: This figure presents estimated impacts of charging station entry on incumbent charging demand at different distance bands. In (a), entrants belong to the same charging network and same standard as incumbents. In (b), entrants belong to a different charging network and are on different standards than incumbents. The outcome variable is utilization rate measured as the fraction of hours in each month that public charging stations are observed to be in use.

4 Impact of Entry that Completes Electrification of Routes

Figure 6 provides intuition for our hypothesis of how individual charging stations may exert positive spillovers on other charging stations. Between the two cities s and t, three incumbent charging stations are represented by the open circles. A potential fourth entrant could generate positive spillovers in charging demand for incumbents by connecting the route $s - t$ for a given EV range. We use the 493 Urbanized Areas (UA) defined by the U.S. Census as the set of potential origin and destination cities and query the geographic coordinates of the driven route between each pair of cities from a routing software package. We link Level 3 charging stations in our dataset with the set of routes connecting UAs; a charging station is considered "on" a route if it is within .5 miles from the road or highway.

Figure 6: Illustration of how stations may exert positive spillovers on other stations



Notes: This figure depicts two cities, s and t, with three charging stations represented by the open circles. For a given EV with range long enough to travel between each adjacent pair of stations but not much beyond, the route $s - t$ is not connected. A possible fourth entrant could connect the route $s - t$ and may generate positive spillovers in charging demand on the incumbent charging stations.

We investigate the impact of entrants on incumbents along shared routes using data on check-ins with the following estimating equation:

$$y_{rt} = \beta_0 + \beta_d \text{Connected}^d_{rt} + \gamma_r + \gamma_t + u_{rt}, \tag{2}$$

where r denotes a route and y_{rt} is average utilization of incumbents on route r. Route fixed effects γ_r control for unobservables at the route level that are fixed over time, such as the overall importance of a certain route or the "greenness" of people who live in cities that are connected by route r. Time (month) fixed effects γ_t control for unobservables that are fixed for a given time period, such as seasonal variation in demand for road trips. The variable Connected^d is 0 if the maximum distance from one station to the next along a route exceeds d, and 1 if there is a charging station every d miles along the route. The interpretation of β_d is the impact of a route becoming connected at distance d on incumbent utilization. The identifying assumption for the causal interpretation of β_d is that unobserved demand shocks that motivate entry are uncorrelated with whether and when the route becomes connected. For example, charging stations may enter because they observe or expect (unobserved to the researchers) rising demand for charging. Our identifying assumption and

interpretation of β_d is that any discontinuous increase in utilization for incumbents is due to the connection event, and demand would not have increased if not for the last entrant who connects the route.

We estimate an event study specification of Equation 2 for routes becoming connected, for a range of distances d:

$$y_{rt} = \beta_0 + \sum_{j=1}^{J} \beta_j (\text{Lead } j)^d + \sum_{k=0}^{K} \beta_k (\text{Lag } k)^d + \gamma_r + \gamma_t + u_{rt}, \tag{3}$$

where y_{rt} is the average number of check-ins at stations on route r in period t, and β_j is the impact of the route connection event on the average number of driver check-ins at incumbent stations j months before a route becomes connected at d miles. Similarly, β_k is the impact of the route connection event on the average number of driver check-ins at incumbent stations k months after a route becomes connected at d miles. Figures 7 – 9 present event study graphs for each of the three charging standards, Tesla, Chademo, and Combo, respectively, using data on station check-in counts across the U.S. from 2011 to 2022.

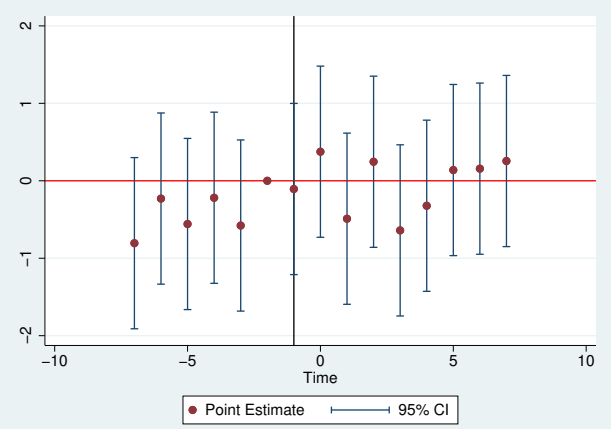
Figure 7 presents event study graphs for the Tesla network. The title of each subfigure is the distance of the route connection event. Subfigures (a) and (b) show check-in counts staying fairly level after a route becomes connected at 30 or 50 miles. Subfigures (c) – (e) show that when routes become connected at 70 to 120 miles, average check-in counts at incumbent stations increase. Subfigure (f) for 150 miles shows ambiguous impacts of route connection on check-in counts. The subfigures together suggest that stations 70 to 120 miles apart generate additional charging demand at other stations on a route by about .5 visits per station and month, on average, while stations too far apart (150 miles apart) or too close (50 or 30 miles apart) do not generate additional charging demand. All of Tesla's vehicles are long-range EVs (200 to 400 miles of range), and the patterns from the event study are consistent with long-range EV drivers stopping every 70 to 120 miles for recharging on highways.

EVs with the other two charging standards, Chademo and Combo, are not all long-range, and the event study results reflect the different electric ranges of the vehicles. For example, the first-generation Nissan LEAF, which debuted in 2010 on the Chademo Standard, had 80 miles of range. A more recent example, the 2023 electric Mini Cooper, has 110 miles of range and is on the Combo standard. Figures 8 and 9 are similar, showing in Subfigure (b) across both figures that check-in counts rise after a route connection event at 50 miles, while the other panels show little effect of the connection event for other distances. Together, the subfigures suggest stations every 30 to 50 miles

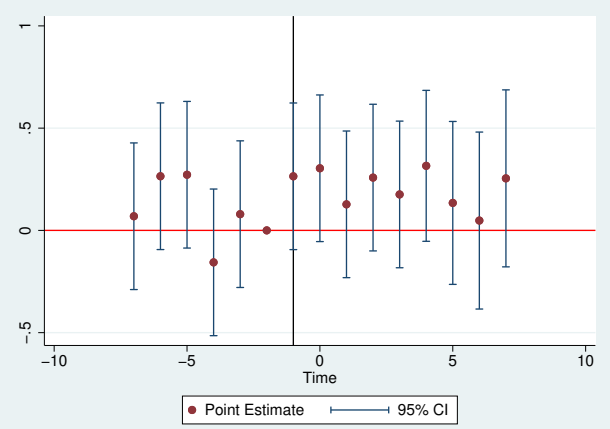
apart generate additional charging demand at other stations along the same route by about .5 visits per station and month, on average, while 70 miles or more would be too far apart for lower-range EVs. These results are consistent with EVs with Chademo and Combo standards having lower electric range on average.

Figure 7: Event studies, Plugshare reviews, Tesla, Monthly

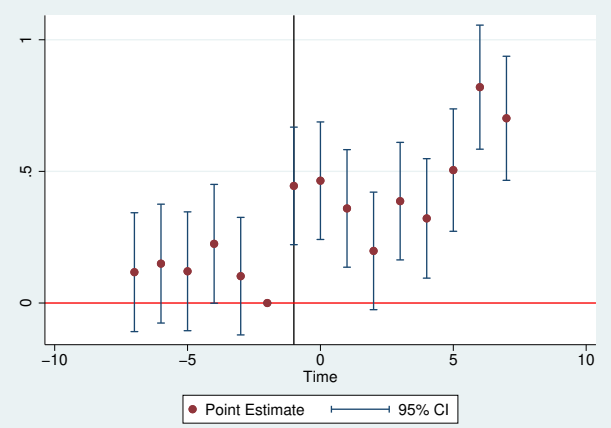
(a) 30 miles



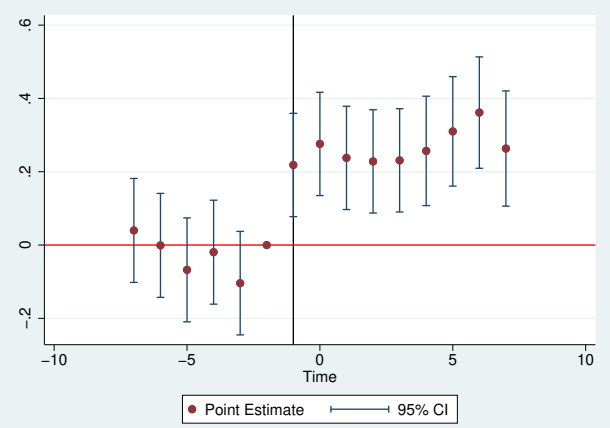
(b) 50 miles



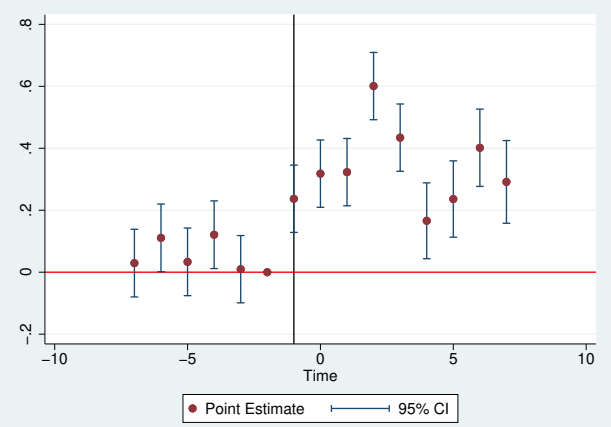
(c) 70 miles



(d) 100 miles



(e) 120 miles



(f) 150 miles

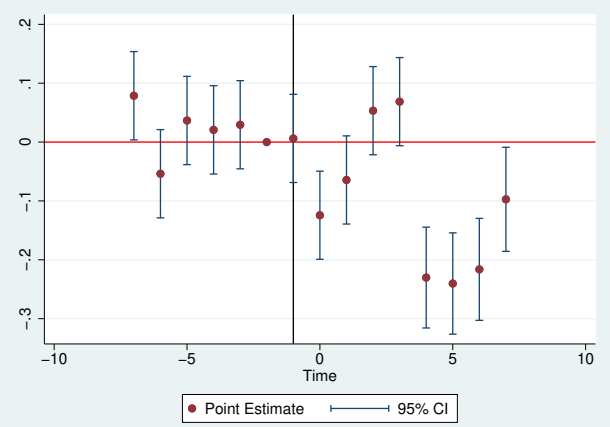
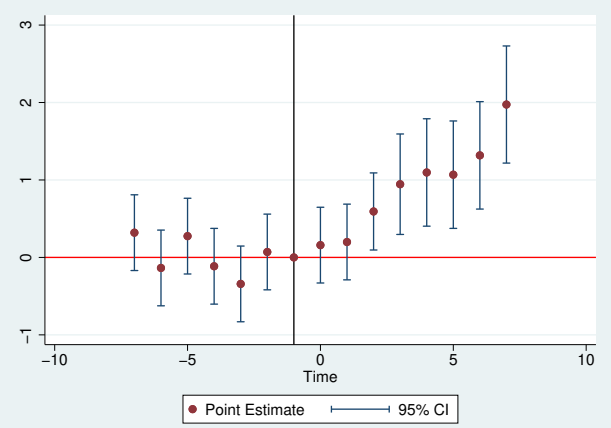
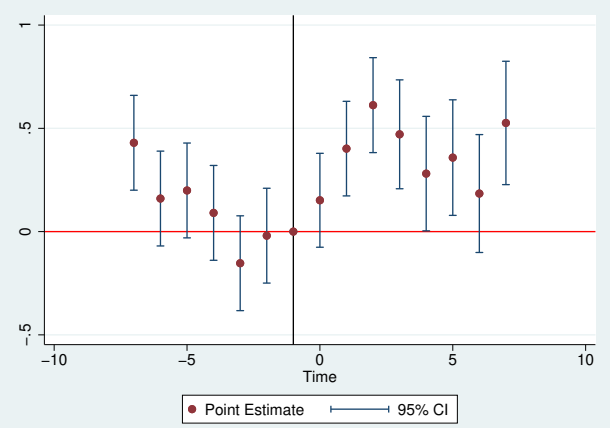


Figure 8: Event studies, Plugshare reviews, Chademo, Monthly

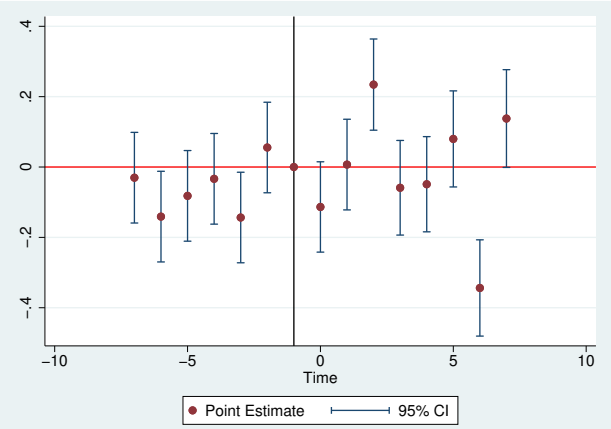
(a) 30 miles



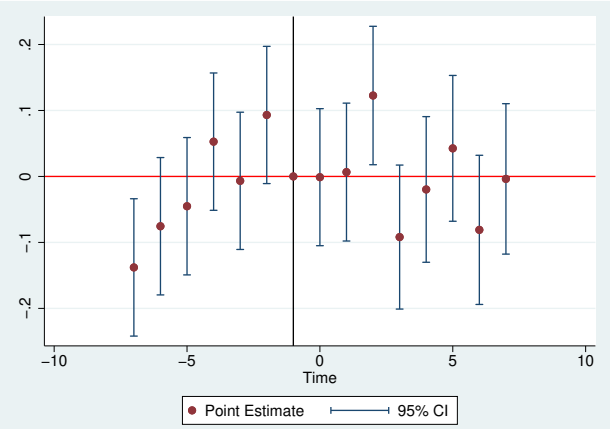
(b) 50 miles



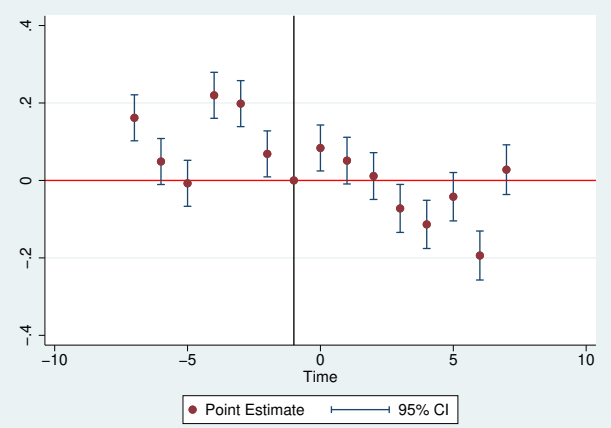
(c) 70 miles



(d) 100 miles



(e) 120 miles



(f) 150 miles

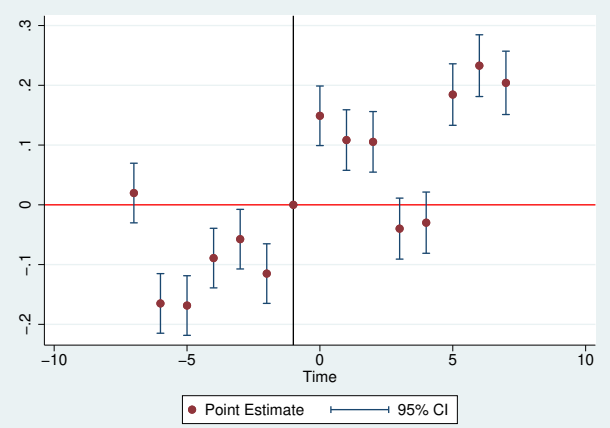
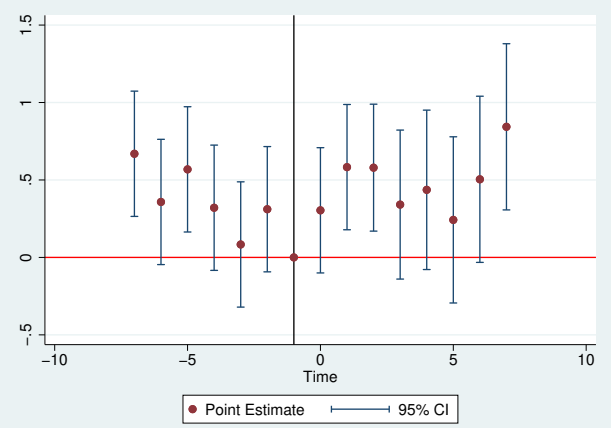
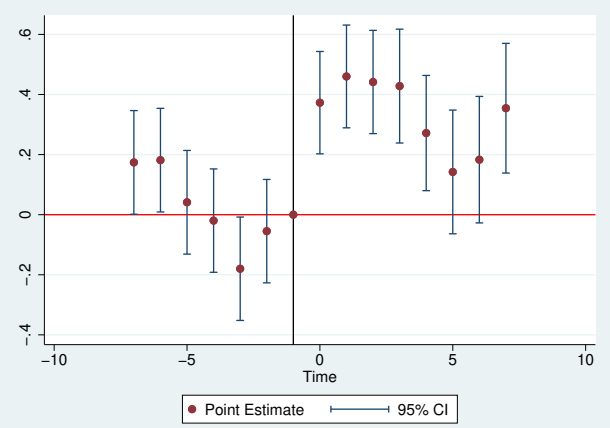


Figure 9: Event studies, Plugshare reviews, Combo, Monthly

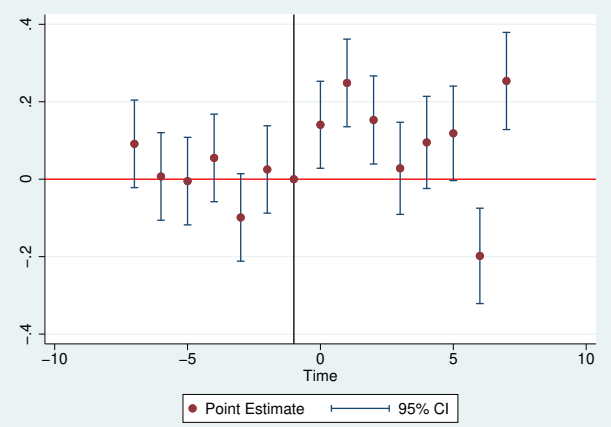
(a) 30 miles



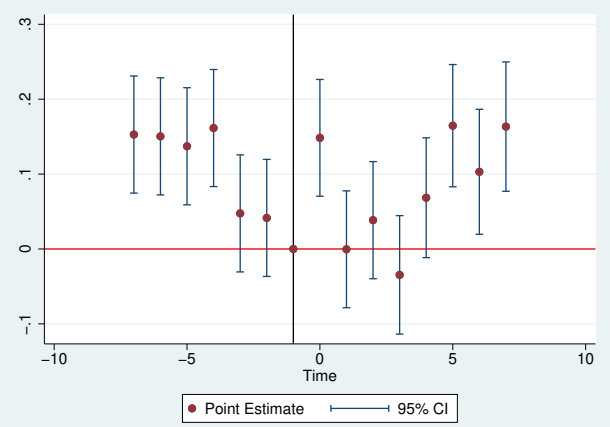
(b) 50 miles



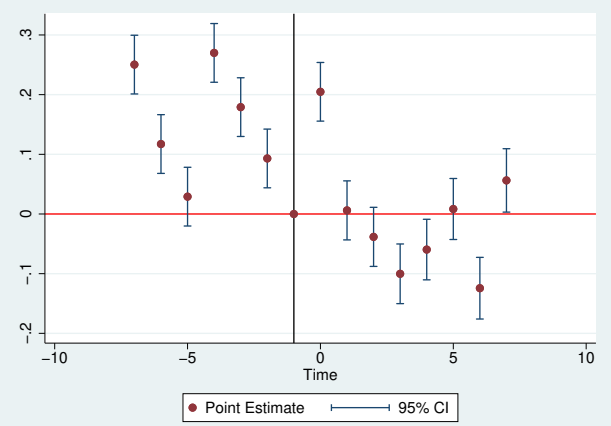
(c) 70 miles



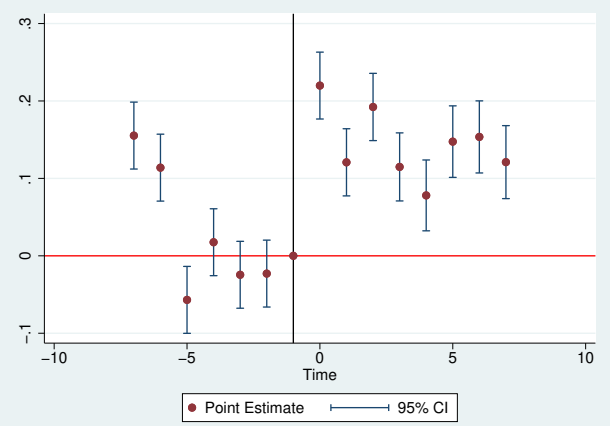
(d) 100 miles



(e) 120 miles



(f) 150 miles



5 Site and Network Entry Motives

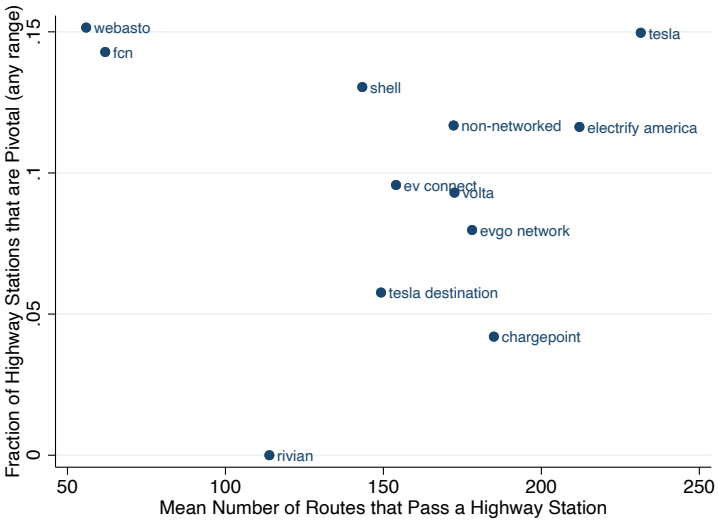
How much of the entry spillovers are internalized by the market placement of charging stations? A station may be owned by either the site host or the charging network. From a social planner's point of view, one key potential difference between the two types of owners is that site hosts may put more weight on the benefit of a charging station to their site (or group of sites if the site host is a chain of stores), while the network may also consider the contribution of a charging station to the rest of the network and thus internalize more entry spillovers.

The costs, benefits, and flows of payments differ by owner type, and some networks also offer hybrid models where costs and charging revenue are shared. If a station is owned by the site host, then the site host pays a recurring network fee. The network fee covers the benefit of being listed in the network's driver maps and a bundle of software and business services. If a station is owned by the network, then the network pays the site host a recurring rent or lease payment for the space occupied by the charging equipment. The owner of the station, either the site host of the network, pays the upfront fixed costs for equipment, permitting, and installation as well as the recurring costs of owning and operating the station such as maintenance and electricity. The owner of the station receives any charging revenue earned from driver visits. The site host also earns any ancillary benefits such as green glow, reputation gains, and additional foot traffic and sales.

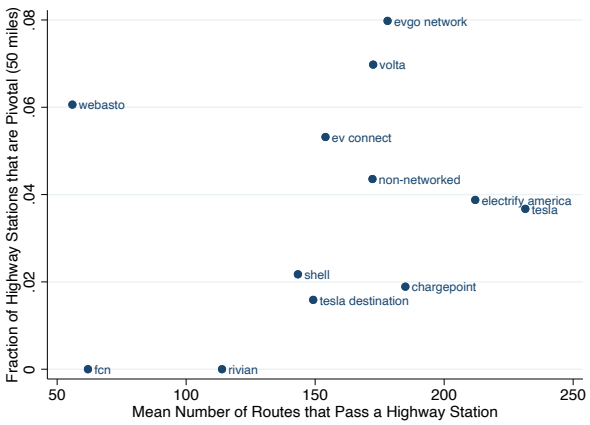
Some charging networks are publicly listed companies and thus state their business model very clearly in their filings to the U.S. Securities and Exchange Commission. However, not all networks are publicly listed, and some networks offer hybrid options, with some site-owned stations, network-owned stations, as well as co-owned stations with differing degrees of cost-and-revenue-sharing. Therefore, it is difficult to know the entry motive of an observed charging station entrant without detailed information on the contracts between site hosts and networks for each station. Such a dataset is not possible to obtain, to our knowledge. Therefore, we take a revealed preference approach. For each station, we construct measures of private and network benefits. Each station occupies a point in the 2-D space of site vs. network benefits, and we can compare whether certain networks' stations tend to occupy different regions in this space. We use network centrality to reflect site entry motives, in particular, a version of *betweeness centrality* – between how many pairs of cities does a station sit. For network benefits, we ask for how many pairs of cities is a charging station *pivotal*. A station is pivotal if an EV with a given range is able to travel the route between two cities with a station and unable to travel that route without the station.

Figure 10: Network vs. Site Entry Motives Averaged by Network

(a) All ranges



(b) 50 miles



(c) 150 miles

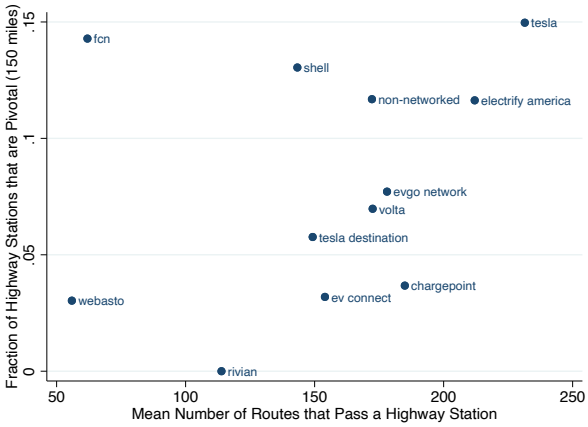


Figure 10 plots networks by the fraction of their highway stations that are pivotal for any route (network benefit) against the mean number of driving routes (shortest path between two cities in a car) that pass a highway station (site benefit). Subfigure (a) averages over all EV ranges, and Subfigures (b) and (c) plot network positions for 50 miles of range and 150 miles of range, respectively. EV range enters the construction of the y-axis position of networks on these graphs because whether a station is pivotal for the route depends on the given EV range. The position of networks along the x-axis do not change across subfigures because whether a driving route passes through a station does not depend on EV range.

Tesla and Electrify America appear to be trying to maximize the number of routes that they connect across the U.S., which is reflected in their stations with high site as well as network

benefits. In contrast, ChargePoint, for example, publicly states that their business model is to not own charging assets and allow their site host partners to optimize for themselves. ChargePoint focuses on providing equipment and software to help site hosts, and this strategy is reflected in their stations having relatively low network contributions yet fairly high site benefits. Networks seem to specialize in serving EVs with different electric ranges. For example, EVgo stations have high network contributions at the 50-mile range, while Tesla and Electrify America stations have high network contributions at the 150-mile range. This analysis shows that the joint entry decision between site hosts and networks, along with different business strategies of the networks, lead to very different network configurations. This heterogeneity across networks suggest that a uniform subsidy is unlikely to meet any social planner objectives that prioritize particular spatial arrangements of stations. For example, if the U.S. government wants stations to serve all EV ranges, including the lowest ones, then a uniform subsidy would subsidize networks focusing on longer-range EVs as well. Whether government policy should aim to serve all EV ranges, including the lowest ones, depends on consumer preferences and welfare weights, and could be studied with a structural approach with a model.

6 Conclusion

Policy makers at the national, state, and local levels have established ambitious goals for promoting EV sales, often going as far as promising to completely phase out internal combustion engine (ICE) vehicles. EV sales are rising quickly compared to traditional gas vehicles, but to reach these ambitious EV adoption goals—take for example California's 2035 goal of 100% of new cars and light trucks sales being zero-emission vehicles (California Governor, 2020)—the growth rate must accelerate (Cui and Hall, 2022). Many subsidy programs for charging stations are also spatially targeted, sometimes with the every-50-mile policy as in the U.S. IIJA. In some other cases, policymakers try to directly choose where to place charging stations using transportation metrics such as traffic flow or number of stations per EV for a given area. These spatially targeted subsidies can enhance social welfare if the market provision of EV charging stations inefficiently allocates stations in space, or in other words, if the market-provided charging network has holes. We study the U.S. EV charging industry to test for the presence of entry complementarities across charging stations. We find evidence of entry complementarities using two different empirical specifications. In ongoing work, we are investigating whether and how much firms already internalize these entry complementarities in their observed location choices.

References

Arcidiacono, P., Ellickson, P. B., Mela, C. F., and Singleton, J. D. (2020). The competitive effects of entry: Evidence from supercenter expansion. *American Economic Journal: Applied Economics*, 12(3):175–206.

Bresnahan, T. and Reiss, P. (1990). Entry in monopoly markets. *Review of Economic Studies*, 57:531–553.

Bresnahan, T. F. and Reiss, P. C. (1991). Entry and competition in concentrated markets. *Journal of political economy*, 99(5):977–1009.

Cachon, G. P. and Kök, A. G. (2007). Category management and coordination in retail assortment planning in the presence of basket shopping consumers. *Management Science*, 53(6):934–951.

California Governor (2020). Executive Order N-79-20. `https://www.gov.ca.gov/wp-content/uploads/2020/09/9.23.20-EO-N-79-20-text.pdf`.

Cui, H. and Hall, D. (2022). Annual update on the global transition to electric vehicles: 2021. Technical report, International Council on Clean Transportation.

Dorsey, J., Langer, A., and McRae, S. (2022). Fueling alternatives: Gas station choice and the implications for electric charging. Technical report, National Bureau of Economic Research.

Gillingham, K., Ovaere, M., and Weber, S. M. (2021). Carbon policy and the emissions implications of electric vehicles. Technical report, National Bureau of Economic Research.

Goolsbee, A. and Syverson, C. (2008). How do incumbents respond to the threat of entry? evidence from the major airlines. *The Quarterly journal of economics*, 123(4):1611–1633.

Holland, S. P., Mansur, E. T., Muller, N. Z., and Yates, A. J. (2016). Are There Environmental Beneftis from Driving Electric Vehicles? The Importance of Local Factors. *American Economic Review*, 106(12):3700–3729.

Holland, S. P., Mansur, E. T., and Yates, A. J. (2022). Decarbonization and electrification in the long run. Technical report, National Bureau of Economic Research.

Holmes, T. J. (2011). The diffusion of wal-mart and economies of density. *Econometrica*, 79(1):253–302.

Houde, J.-F. (2012). Spatial Differentiation and Vertical Mergers in Retail Markets for Gasoline. *American Economic Review*, 102(5):2147–2182.

International Energy Agency (2022). World Energy Investment 2022. `https://www.iea.org/reports/world-energy-investment-2022`.

Jia, P. (2008). What happens when wal-mart comes to town: An empirical analysis of the discount retailing industry. *Econometrica*, 76(6):1263–1316.

Li, J. (2019). Compatibility and Investment in the U.S. Electric Vehicle Market. Working Paper.

Li, S., Tong, L., Xing, J., and Zhou, Y. (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.

Mazzeo, M. J. (2002). Product choice and oligopoly market structure. *RAND Journal of Economics*, pages 221–242.

Nishida, M. (2015). Estimating a model of strategic network choice: The convenience-store industry in okinawa. *Marketing Science*, 34(1):20–38.

Seim, K. (2006). An Empirical Model of Firm Entry with Endogenous Product-Type Choices. *The Rand Journal of Economics*, 37(3):619–640.

Sinyashin, A. (2021). Optimal Policies for Differentiated Green Products: Characteristics and Usage of Electric Vehicles. Unpublished.

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

Whinston, M. D. and Collins, S. C. (1992). Entry and competitive structure in deregulated airline markets: an event study analysis of people express. *The RAND Journal of Economics*, pages 445–462.

Online Appendix

Table A1: Number of Vehicle Trip by Trip Distance; 2017 NHTS

Trip Distance	Travel Day Vehicle Trips		
	Sample Size	Sum (Millions)	Percent
Less than 0.5 miles	31,851	11,063	5
1 mile	98,955	36,078	16.4
2 miles	84,856	30,430	13.8
3 miles	64,205	22,820	10.4
4 miles	48,361	17,357	7.9
5 miles	37,449	13,276	6
6 - 10 miles	106,830	38,153	17.3
11 - 15 miles	50,791	18,597	8.4
16 - 20 miles	28,913	10,999	5
21 - 30 miles	27,860	10,747	4.9
31 miles or more	31,228	10,895	4.9
Not ascertained	43	16	0
All	611,342	220,430	100

Notes: Vehicle trips are defined as trips by a single privately-operated vehicle, regardless of the number of people traveling in the vehicle.

Table A2: Number of Vehicle Trip by Purpose; 2017 NHTS

Trip purpose summary	Travel Day Vehicle Trips		
	Sample Size	Sum (Millions)	Percent
Home	205,765	75,569	34.3
Work	92,401	36,568	16.6
School/Daycare/Religious activity	16,288	6,789	3.1
Medical/Dental services	11,568	3,301	1.5
Shopping/Errands	134,052	42,977	19.5
Social/Recreational	52,879	18,616	8.4
Transport someone	44,996	18,746	8.5
Meals	43,348	14,832	6.7
Something else	10,045	3,031	1.4
All	611,342	220,430	100

Notes: Vehicle trips are defined as trips by a single privately-operated vehicle, regardless of the number of people traveling in the vehicle.

Table A3: Number of Person Trips by Transportation Mode; 2017 NHTS

Transportation Mode Used on Trip	Travel Day Person Trips		
	Sample Size	Sum (Millions)	Percent
Walk	81,288	38,947	10.5
Bicycle	8,034	3,575	1
Car	396,931	156,940	42.3
SUV	229,466	84,659	22.8
Van	60,463	27,857	7.5
Pickup truck	108,303	35,115	9.5
Golf cart / Segway	826	186	0.1
Motorcycle / Moped	2,088	835	0.2
RV (motor home, ATV, snowmobile)	814	212	0.1
School bus	11,313	7,038	1.9
Public or commuter bus	6,616	5,300	1.4
Paratransit / Dial-a-ride	624	393	0.1
Private / Charter / Tour / Shuttle bus	1,581	814	0.2
City-to-city bus (Greyhound, Megabus)	120	69	0
Amtrak / Commuter rail	1,148	794	0.2
Subway / elevated / light rail / street car	3,326	3,350	0.9
Taxi / limo (including Uber / Lyft)	2,813	1,849	0.5
Rental car (Including Zipcar / Car2Go)	2,006	780	0.2
Airplane	1,823	639	0.2
Boat / ferry / water taxi	458	176	0
Something Else	3,515	1,617	0.4
I prefer not to answer	2	0	0
I don't know	13	7	0
Not ascertained	1	0	0
All	923,572	371,152	100

Notes: A person trip is defined as a trip from one address to another by one person using any mode of transportation.

Table A4: Number of Households by Household Vehicle Count; 2017 NHTS

Count of Household Vehicles	Number of Households		
	Sample Size	Sum (Thousands)	Percent
0	6,249	10,567	8.9
1	41,534	39,648	33.5
2	49,936	39,125	33.1
3	20,267	17,598	14.9
4	7,562	7,194	6.1
5+	4,148	4,077	3.4
All	129,696	118,208	100

Notes: The 2017 NHTS weights its household data based on control totals found in the American Community Survey (ACS).