

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

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[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.

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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 environmental

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

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 EVs. 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 the following empirical test for the presence of entry spillovers. We investigate the impact of entry events on incumbent charging station utilization located along the same route. 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 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 again at 150 miles, but we find no discernible effects for distances between 70 miles and 120 miles. 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 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. Furthermore, our results suggest that different charging networks may be prioritizing serving EVs with certain driving ranges. Therefore, our findings indicate that 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 Industry Background

2.1 EV Market and Recharging

The EV market has grown dramatically since their modern revival. After Tesla first unveiled the Roadster, a high-priced electric sports car, 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 50% and two-thirds of new sales being electric by 2030 and 2032 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, and 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.

2.2 Infrastructure to Charge EVs

The analog of gas stations for gasoline-powered cars is charging stations for EVs. Options for recharging EVs range in speeds (see Appendix Table 1). 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 can take 1 to 2 hours for PHEVs and 4 to 10 hours for BEVs. The fastest charging speed is called Level 3. Although the slowest Level 3 charging station may be as low as 50kW of power output, the fastest Level 3 charging stations range from 150kW to as much as 350kW with some models allowing up to 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.

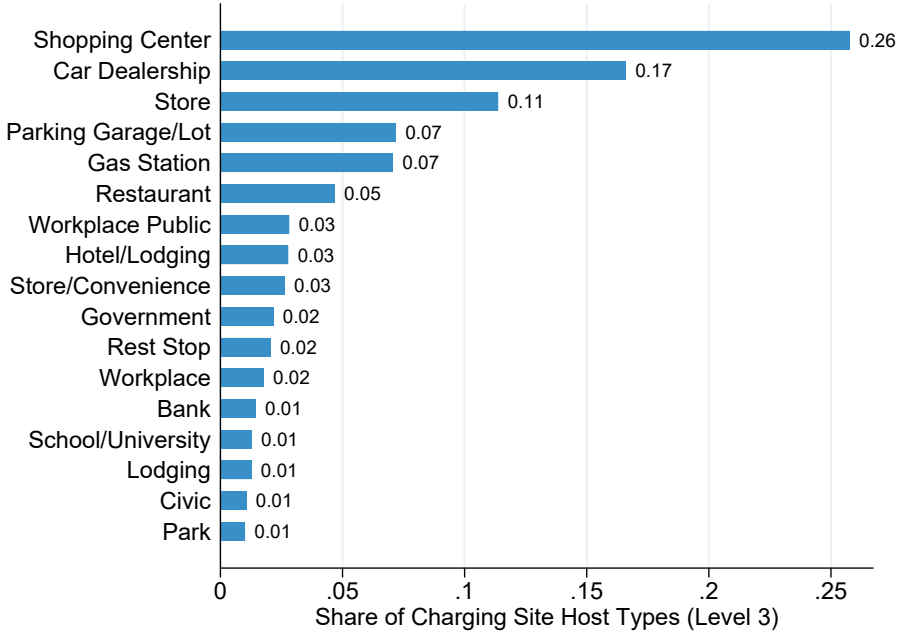
2.3 EV Charging Industry

We define charging stations as a collection of charging equipment located at a site host. Unlike most gas stations that have their own polygon and their own street address, charging stations are considered points and they do not generally have their own street address. Instead, they are

usually linked to the site host’s street address whose parking space is being offered to host the station. Each charging station location may have one or more EV charging posts which can house multiple connectors (also called plugs) on the same and/or different charging standards.

A charging station may be owned by either a site host or a charging network. Site hosts vary in their primary purpose or business and include a variety of establishments such as shopping malls, stores, parking lots and garages, restaurants, hotels, etc.

Figure 1: Primary Purpose/Business of Charging Site Hosts for Level 3 Chargers (2021/11-2023/07)

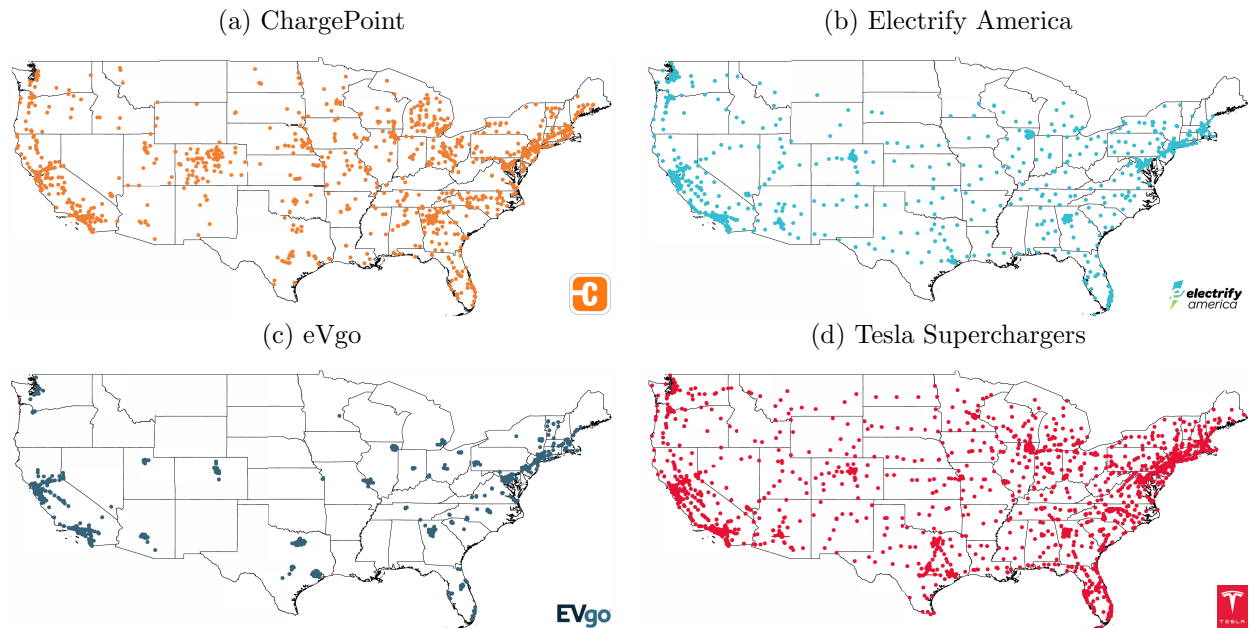


Notes: This figure plots the primary purpose or business of level 3 charging site hosts in descending order of their share out of the total count of Level 3 stations from November 2021 to July 2023, obtained from a crowd-sourced 3rd-party app data. The figure is restricted to site host types with shares higher than 1%.

Figure 1 shows how charging site hosts for Level 3 chargers vary in their main business activity. Site hosts typically own a single charging station (or one per site if the site host is a chain of businesses). Charging networks may own and operate a group of charging stations. Charging networks in the U.S. differ in their build-out strategies (see Figure 2 for examples) and these differences seem to relate to how ownership is structured within the network and/or the business model that the network has chosen to adopt. Some charging networks like ChargePoint do not own charging stations or monetize driver utilization of stations. On the other end of the spectrum there are charging networks such as Electrify America which pays for all costs related to the installation of charging stations belonging to its network. There are many hybrid models that exist between these two business models such as eVgo’s network which has a mixed ownership (some stations are

site-host owned while some are owned by eVgo) on its network.

Figure 2: Examples of U.S. Charging Networks in 2023/07; AFDC



Notes: This figure plots Level 3 stations of different charging networks in the U.S. from July 2023, obtained from AFDC.

Charging stations may be non-networked or network affiliated. Non-networked stations provide basic charging functionality without advanced communication, utilization monitoring, or payment capabilities. Non-networked stations are not connected to the internet, while network-affiliated stations are connected to the internet. These advanced communication capabilities allow networked stations to communicate location, access information and pricing directly with EV drivers through the charging network’s driver map or app, monitor utilization and share real-time updates on availability of charging services with drivers, and facilitate payment processing.² Site-host owned stations may or may not be affiliated with a charging network. Charging network owned stations are naturally affiliated with the network that owns and operates them.

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

²See “Charging Infrastructure Procurement and Installation” *Alternative Fuels Data Center* December 16, 2023, URL.

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 National Renewable Energy Laboratory (NREL) and Idaho National Laboratory (INL) estimates that equipment costs for Level 3 chargers can range between \$38,000 and \$90,000 per connector while installation costs per Level 3 charger vary from \$20,000 to \$60,000 (Borlaug et al., 2020). The owner of the station sets pricing for charging at their station and 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.

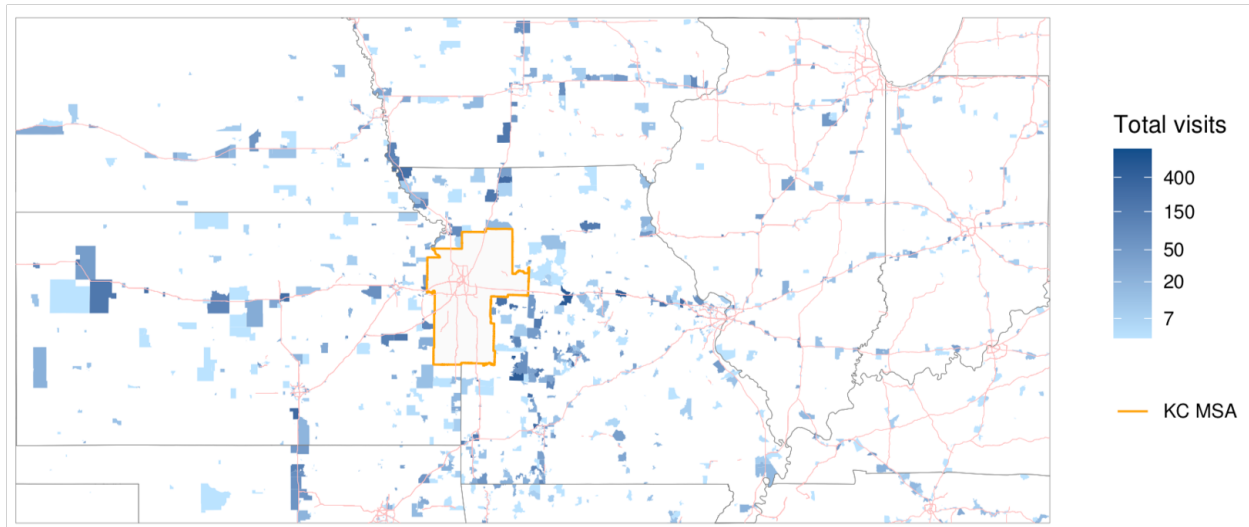
3 Data

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 Appendix Tables 2 through 5. 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 3 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

Figure 3: Visits to Gas Stations by People Who Live in KC, MO, Aug 2020; SafeGraph

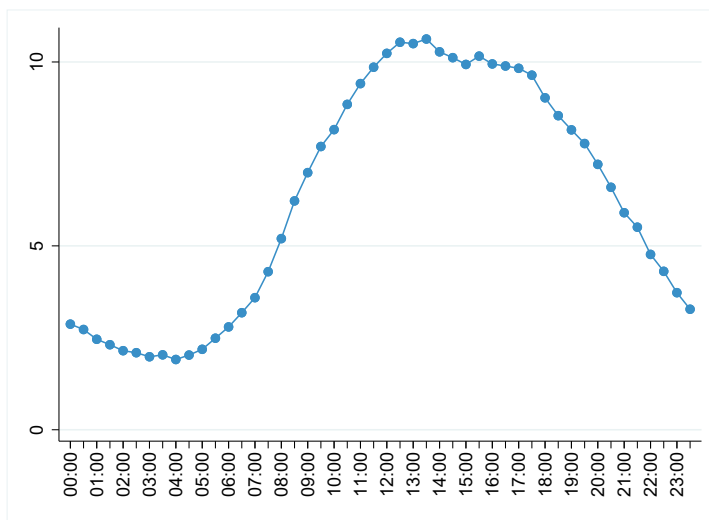


vehicle registration counts in the US by make, model, model year, and trim, at finely disaggregated geographic (census tract) and time (month) levels, from 2012 to 2023. These data on vehicle quantities are very detailed in the vehicle, geography, and time dimensions, which will allow us to merge flexibly 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 2014 to the present. To capture potential entry locations for charging stations, we collected data on highway exits and rest areas from OpenStreetMap and points of interest (POIs) from SafeGraph.

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 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 4: Utilization Profile Averaged over Days

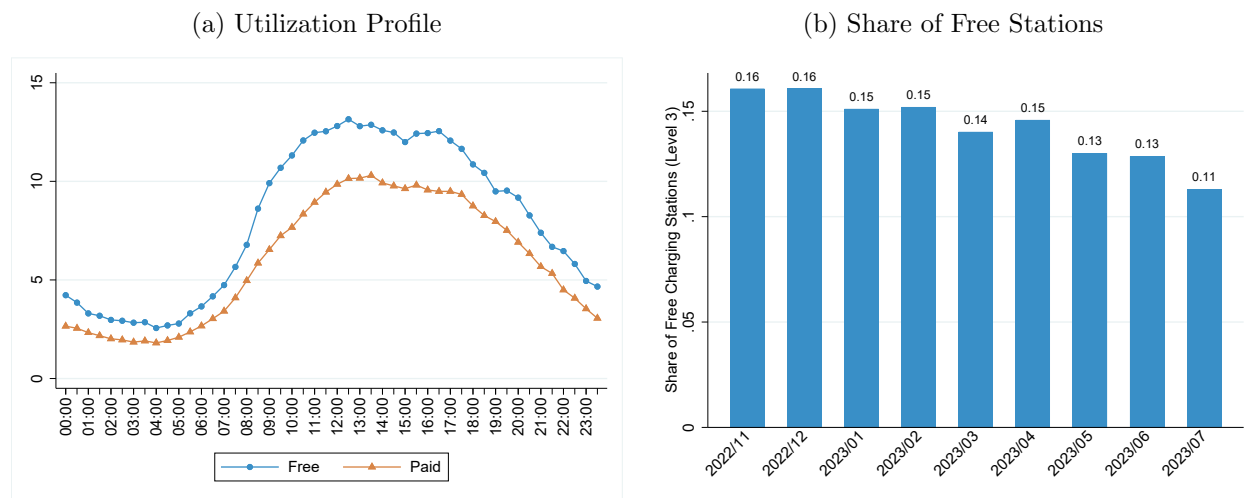


Notes: This figure plots the charging profile of Level 3 stations for one network nationwide between November 2022 and July 2023. The horizontal axis begins at midnight and increments in half-hours. Each point represents the percentage of stations that are in-use at a given time, averaged over days observed between November 2022 and July 2023.

Figure 4 shows the utilization profile throughout the day for one network nationwide, averaged over days observed between November 2022 and July 2023. 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. In each month between November 2021 and July 2023, less than 1% of fast charging stations experienced utilization at full capacity at least in one 30-minute interval. Figure 5 plots nationwide utilization profiles and shares of free and paid stations for the same network. Subfigure (a) demonstrates how charging profile of free versus paid fast public charging stations differ throughout the day, averaged over days observed between November 2022 and July 2023. Free stations are always used more than stations accessible for a fee and this difference is the largest at mid-day when utilization peaks. Subfigure (b) indicates that the share of free fast charging stations

is declining over time on this charging network.

Figure 5: Free vs. Paid Charging Stations (Level 3)



Notes: This figure shows the utilization rates and share of free and paid fast charging stations for one network nationwide between November 2022 and July 2023. Subfigure (a) plots charging profiles for free and paid sites. 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 observed between November 2022 and July 2023. Subfigure (b) shows how during the same period the share of free fast charging stations evolved for this particular network.

Second, we have around 2.4 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 0.27 for cumulative check-in counts and 0.22 for new monthly check-in counts at the census tract level. 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.

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 full green 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 Adjusted Urbanized Areas (AUA) defined by the U.S. Census (shown in Appendix Figure 1) 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 AUAs; a charging station is considered “on” a route if it is within 0.5 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.

4.1 Binary Measure of Route Electrification

We first investigate the impact of entrants on incumbents along shared routes using data on check-ins and defining route electrification with a binary measure that takes on the value of 1 when a route is connected for a given distance with the following estimating equation:

$$y_{rt} = \beta_0 + \beta_d \text{Connected}_{rt}^d + \gamma_r + \gamma_t + u_{rt}, \quad (1)$$

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_{rt}^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.

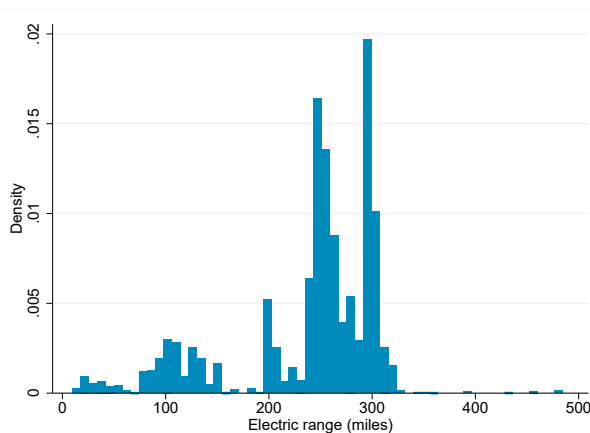
We estimate an event study specification of Equation (1) for routes becoming connected, for a range of distances d :

$$y_{rt} = \beta_0 + \sum_{j=1}^J \beta_j (\text{Lead } j)^d + \sum_{k=0}^K \beta_k (\text{Lag } k)^d + \gamma_r + \gamma_t + u_{rt}, \quad (2)$$

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.

At what driving distances might we expect to see effects of entry on incumbent charging demand along the same route? 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 7: Electric range of EVs that charge at Level 3 stations, 2011-2022

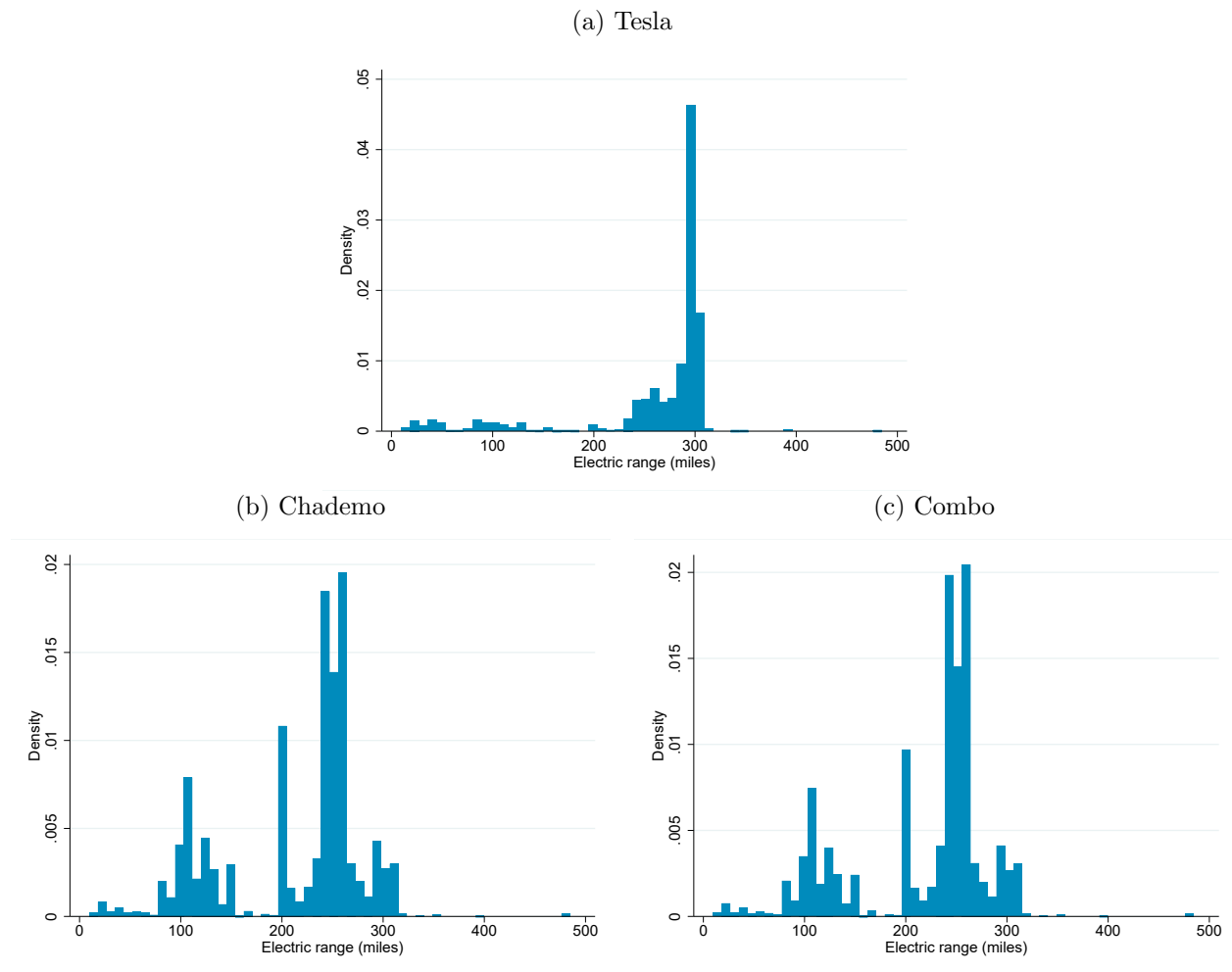


Notes: This figure plots the distribution of electric range of EVs that charge at fast (or Level 3) charging stations between 2011 and 2022 in our check-ins data obtained from a 3rd party app.

Figure 7 plots a histogram of the electric range of EVs that charge at Level 3 (fast) charging stations in our check-ins dataset from 2011 to 2022. A significant share of cars charging at these stations have electric range of 200 to 300 miles. However, car ranges differ by charging standard so we might expect to see effects at different distances for different standards. Figure 8 shows the distribution of electric ranges of vehicles charging at stations of the three fast charging standards, Tesla, Chademo,

and Combo, respectively. Subfigure (a) shows that most EVs that charge at Tesla Superchargers have a long electric range around 300 miles. However, as illustrated in Subfigures (b) and (c), the electric ranges of cars charging at stations with the Chademo and Combo standards have more of a bimodal distribution. While a significant portion of these vehicles have an electric range somewhere between 200 and 300 miles, there is a second smaller group of vehicles with electric range around 100 miles. Figure 8 suggests that while we might expect to see positive spillovers from entry only at longer distances for Tesla stations, for the Chademo and Combo standards we might expect to see such effects also at shorter traveling distances.

Figure 8: Electric Range of EVs Charging at Fast Charging Stations, by Charging Standard

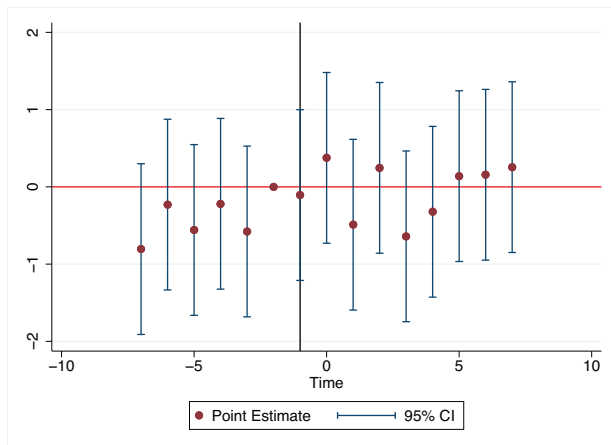


Notes: This figure plots the distribution of electric range of EVs that charge at fast (or Level 3) charging stations between 2011 and 2022 by charging standard.

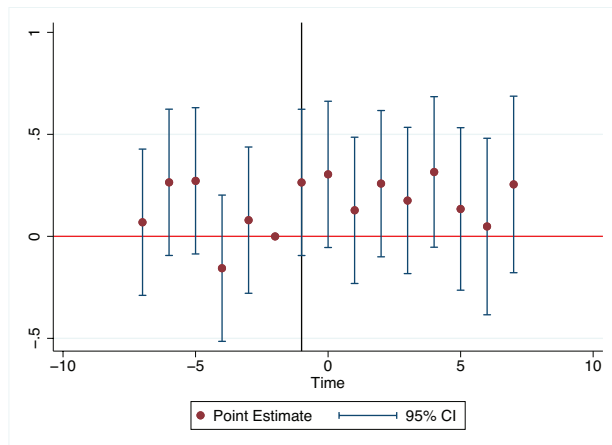
Figures 9 – 11 present event study graphs for each of the three charging standards, Tesla, Chademo, and Combo, respectively, using data on station check-in counts across the U.S. from 2011 to 2022.

Figure 9: Event studies, Station check-ins, Tesla, Monthly

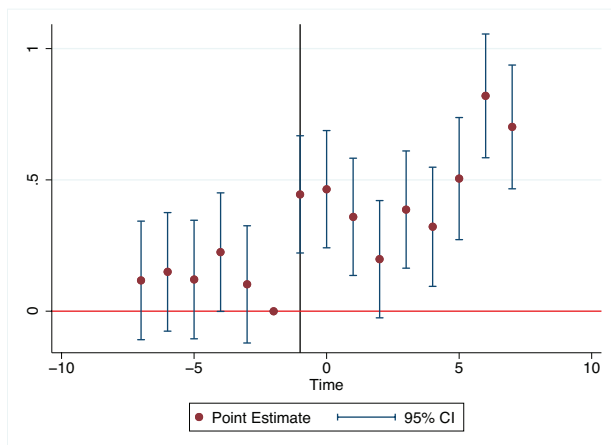
(a) 30 miles



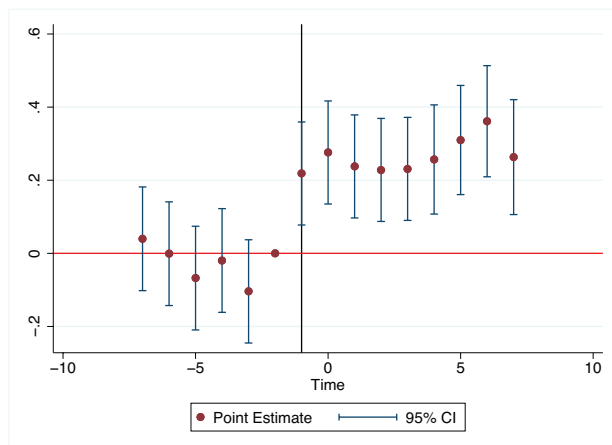
(b) 50 miles



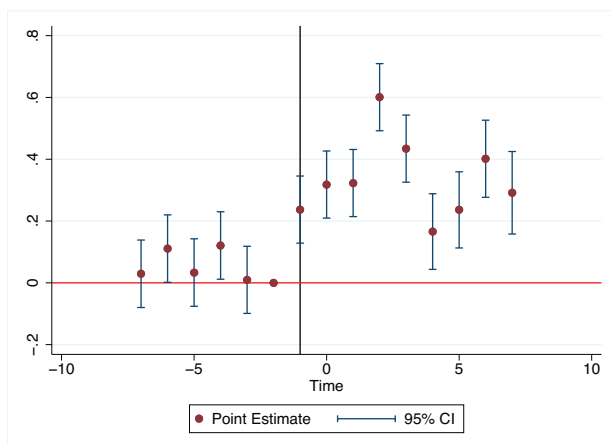
(c) 70 miles



(d) 100 miles



(e) 120 miles



(f) 150 miles

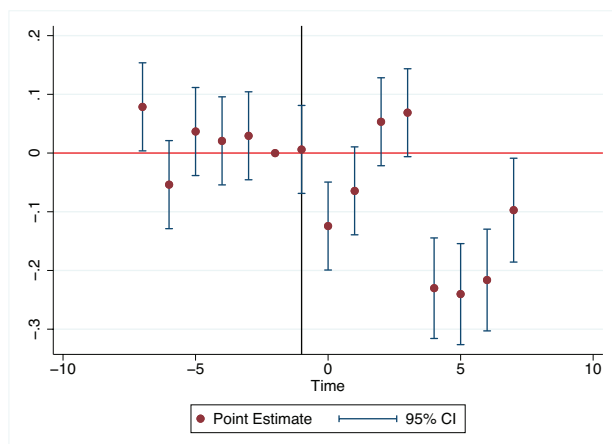


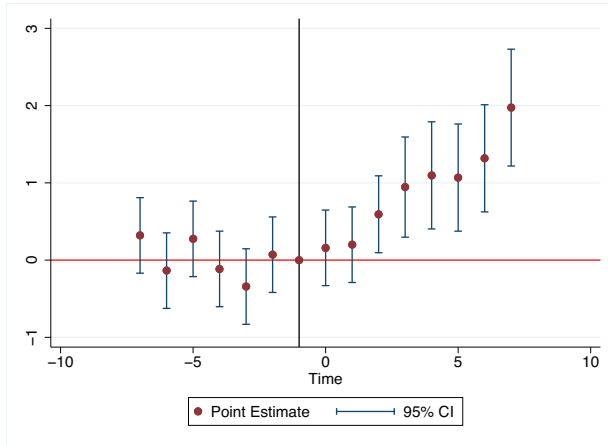
Figure 9 presents event study graphs for the Tesla network. The title of each subfigure is the distance of the route connection event. Subfigures (a) and (b) show check-in counts staying fairly level after a route becomes connected at 30 or 50 miles. Subfigures (c) – (e) show that when routes become 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 0.5 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 Figure 8 indicates that the majority of EVs charging at Tesla stations have an electric range around 300 miles. 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 as demonstrated by Figure 8, 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 10 and 11 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, until 150 miles where again the results indicate a rise in station visits. Together, the subfigures suggest stations every 30 to 50 miles apart as well as 150 miles apart generate additional charging demand at other stations along the same route by about 0.5 visits per station and month, on average, and 70 miles to 120 miles would not generate additional charging demand at incumbent stations. These results are consistent with some EVs charging at stations with Chademo and Combo standards having a lower electric range on average and another of group of longer-range vehicles using the same stations.

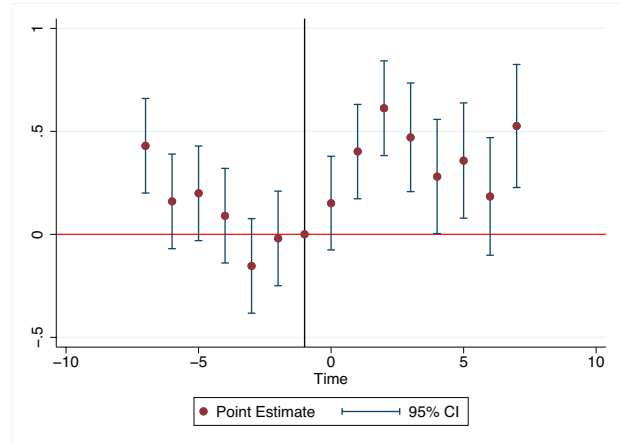
In our first test for entry spillovers we defined route connectedness using a simple binary measure that takes on the value of 1 when a route became electrified for a given traveling distance. However, such a measure treats any additional stations placed along a route that is already connected as if they have no value for EV drivers. Furthermore, a simple binary measure cannot take into account the spatial arrangement of stations along a route beyond a route becoming electrified. Accordingly, next we develop a continuous measure that accounts for not only whether a route is electrified, but also the idea that additional charging stations may reduce congestion and ease range anxiety.

Figure 10: Event studies, Station check-ins, Chademo, Monthly

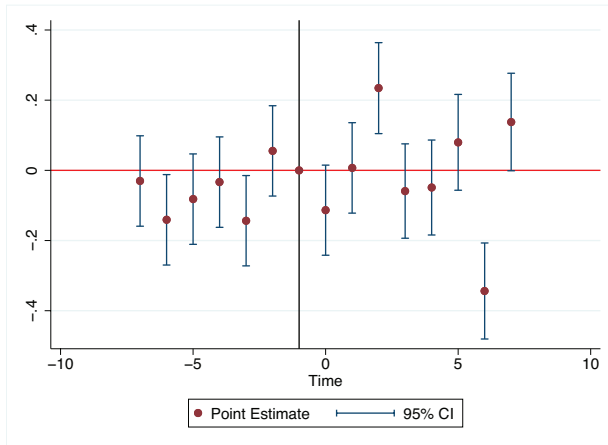
(a) 30 miles



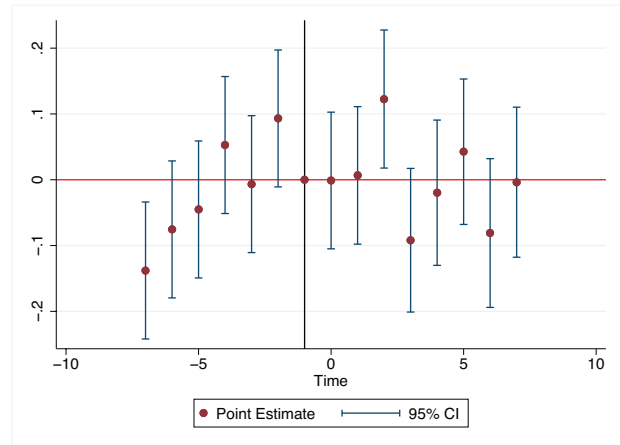
(b) 50 miles



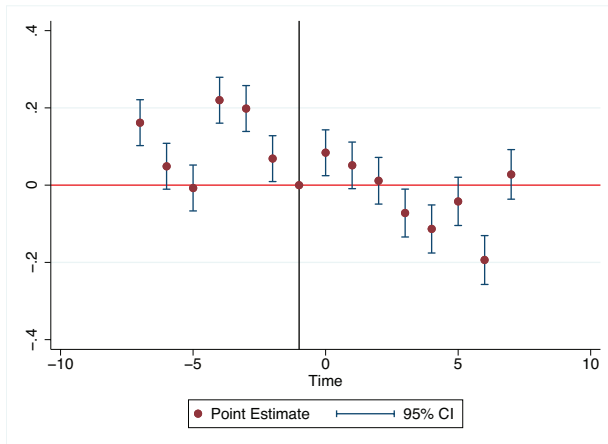
(c) 70 miles



(d) 100 miles



(e) 120 miles



(f) 150 miles

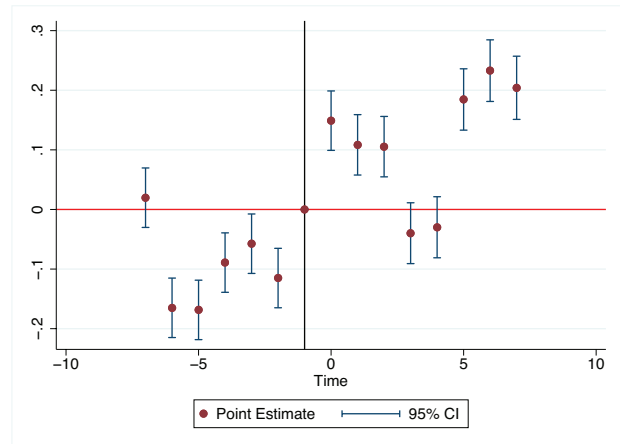
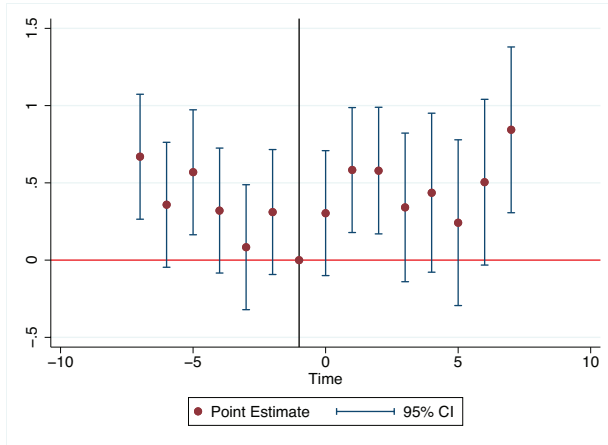
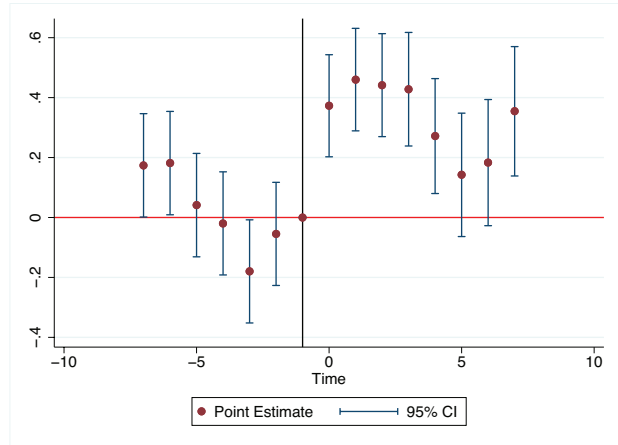


Figure 11: Event studies, Station check-ins, Combo, Monthly

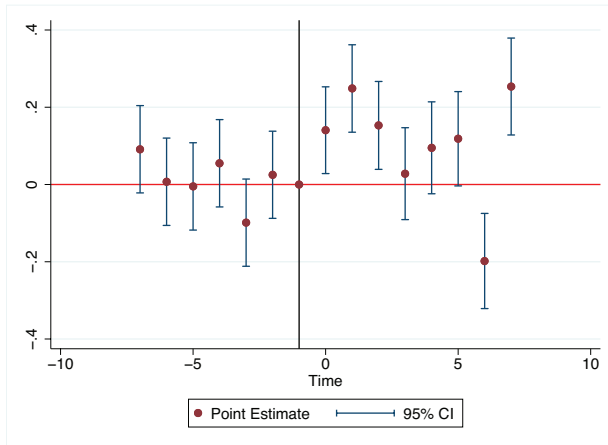
(a) 30 miles



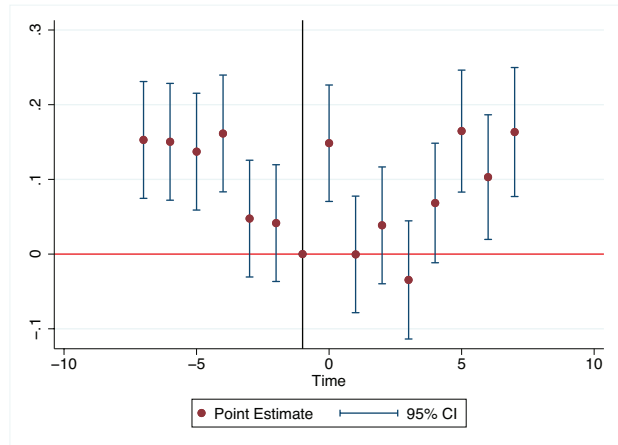
(b) 50 miles



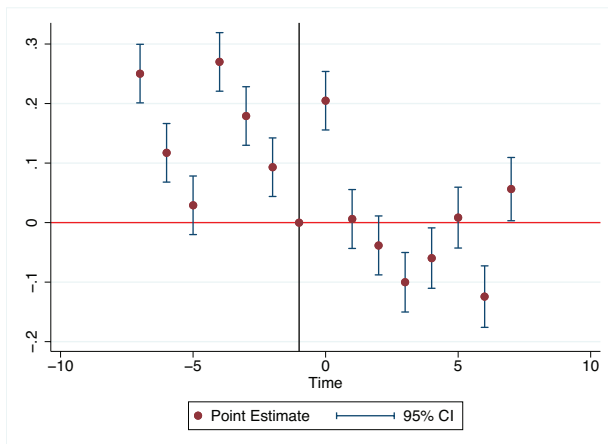
(c) 70 miles



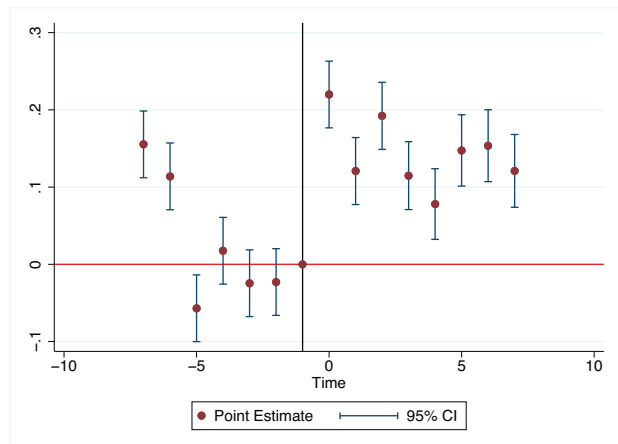
(d) 100 miles



(e) 120 miles



(f) 150 miles

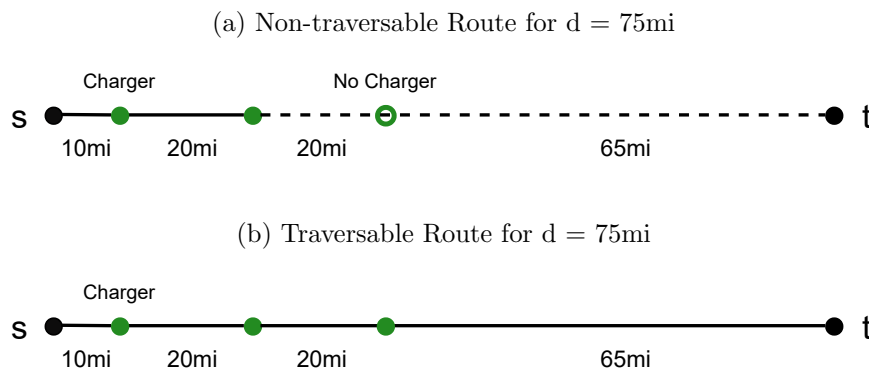


4.2 Continuous Measure of Route Electrification

In what follows, we first develop a micro-founded model of EV suitability of routes. Then, using this modeling framework, we derive a continuous measure for routes which accounts for route traversability, the total number of chargers on a route, and the degree of dispersion of connectors on a route.

Model Setup. We define a route, r , as a segment between a and b , that is $r = [a, b]$, where $a, b \in \mathbb{R}$. Assume that there are E entry locations along a route, each entry location is indexed by e and each entry point has a location l_e which is a point on the segment ($l_e \in r$). Assume that each entry location e has c_e chargers, where $c_e \in \mathbb{N}$. As such, entry locations may or may not have installed chargers. Suppose that EVs have mean battery range b . Then, an entry location e is said to be in range of a vehicle at point $x \in r$ if its range exceeds the distance from the entry point's location or $|x - l_e| \leq b$. It follows that a charger is then in range of a vehicle at point $x \in r$ if the entry point is within the range of the vehicle and it has a charger or $\exists e \in E, |x - l_e| \leq b$ and $c_e > 0$.

Figure 12: Illustration of routes that are traversable vs. not traversable



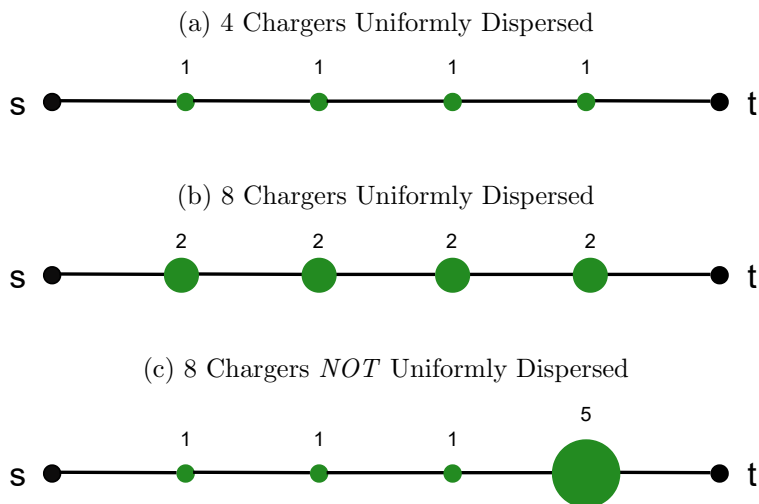
Traversability. Figure 12 provides intuition for our first objective for the continuous measure of route electrification which is to account for whether a route is traversable or not for a given driving distance. Subfigure (a) illustrates a route that is not traversable at $d = 75$ miles since the maximum distance between two adjacent incumbent stations along the route between cities s and t is longer than 75 miles. Subfigure (b) shows the same route between cities s and t after a new station enters at the potential entry location indicated by the empty green circle in subfigure (a), resulting in the maximum distance between two adjacent stations being reduced to less than 75 miles, making the route now traversable for $d = 75$. The continuous measure accounts for the probability that a route is traversable for a given driving distance.

Assume that there are E_C entry locations with at least one charger on a given route. Let us define the route start point charger as $e_c = 0$ and the end point charger as $e_c = E_C$. Suppose an EV starts traveling the route with a full battery capacity. Assume the vehicle were to stop at each e_c to recharge the car's battery, resulting in a range b_{e_c} that is random and is distributed according to F , i.e., $b_{e_c} \sim F$. At each stop for recharge, the vehicle gets a shock to its range which is i.i.d. This assumption reflects the impact of factors such as temperature, altitude, driving speed, traffic conditions, or simply a partial recharge. For example, extremely cold temperatures can reduce the EV battery's output. Similarly, EVs may require more energy to travel at higher altitudes, decreasing the vehicle's overall electric range. Under these assumptions, the probability that a route is traversable without any range issues is given by

$$\prod_{e_c}^{E_C-1} \mathbb{P}(l_{e_c+1} - l_{e_c} < d_{e_c}) = \prod_{e_c}^{E_C-1} (1 - F(l_{e_c+1} - l_{e_c})), \quad (3)$$

where F is the cumulative distribution function (cdf) of b_{e_c} . For a given cdf F this is computable and provides a measure that will be close to one if the route is easily traversable with lots of charging stations and close to zero when there is a large gap without charging opportunities on the route.

Figure 13: Illustration of routes with different charging capacity and degrees of dispersion



Capacity and Dispersion. Figure 13 provides intuition for our second and third objectives for the continuous measure of route electrification which are to account for the total number of fast chargers placed on a route and the degree to which these chargers are dispersed along a route. Subfigure (a) shows a route between cities s and t with 4 uniformly dispersed chargers that is

traversable for a given d distance. In comparison, Subfigure (b) illustrates the same route, but with twice as many chargers at each existing station location. Given the higher capacity, the probability that a vehicle finds an available charger is going to be higher when the route has 8 uniformly dispersed chargers than it would be with only 4 chargers as in Subfigure (a). The continuous measure increases in the total charging capacity along a route, reflecting this relation between the total number of chargers and the average probability that there is an available charger on the route.

The last route depicted in Figure 13, Subfigure (c), shows the same route as in Subfigure (b) with a total of 8 chargers, but the chargers are placed on the route in a highly concentrated fashion instead of being uniformly distributed. The more concentrated distribution of the chargers in Subfigure (c) means that the probability of a charger being available will be higher at the station location with 5 chargers and lower at stations locations with a single charger than it is in Subfigure (b) where each station location has 2 chargers. Furthermore, since routes with more entry locations without any installed chargers, holding traversability and the number of chargers fixed, are less convenient from the EV drivers' point of view, the continuous measure accounts for the probability that vehicles are dispatched to an entry location with at least one charger. Therefore, we are going to measure the model-implied probability of a charger being available at every point along the route and the probability of being randomly assigned to an entry location without a charger.

Assume that EVs that need charging arrive at Poisson rate λ on a grid "arrival points" a_1, \dots, a_n . Suppose vehicles are randomly assigned across entry locations in range of a_j (independently of each other), and within each entry location vehicles are randomly assigned to chargers. Note that EV drivers can be also assigned to an entry location with no installed chargers. Let $E(x)$ denote the set of entry locations that are in range of point x . The probability an EV at point x is assigned to entry location $e \in E(x)$ is then $\frac{1}{|E(x)|}$. This indicates that the 'by exit' Poisson arrival rate at point x for entry location $e \in E(x)$ is $\lambda \frac{1}{|E(x)|}$. Under this set of assumptions, the number of vehicles assigned to an exit, N_e , follows a Poisson distribution with parameter λ_e , where λ_e can be expressed as

$$\lambda_e = \sum_{a_j} \mathbb{1}_{\{|a_j - l_e| \leq d\}} \frac{\lambda}{|E(a_j)|}. \quad (4)$$

For each arrival point we determine whether it is in range of the given entry location and what is the probability at that arrival point that the EV gets dispatched to this given entry location. Since vehicles are randomly assigned to chargers in each entry location, henceforth the number of

cars assigned to a charger i , N_i , then follows a Poisson distribution with parameter $\lambda_i = \lambda_{e_i}/|I_{e_i}|$, where e_i denotes the entry location to which $i \in I_e$ charger belongs to.

Assuming these conditions, we can simulate the probability that at least one charger i in range of point x is available, given by

$$\mathbb{P}(\min_{i \in I(x)} N_i = 0). \quad (5)$$

This probability is increasing in the number of chargers because having more chargers at an entry location decreases their arrival rates λ_i . This probability measure can be integrated over $x \in r$ to compute route accessibility. Given the above assumptions, we can also compute the probability that a vehicle is assigned to an entry location without a charger which can be expressed as

$$\mathbb{P}(v \text{ assigned to } e \in E(x) \setminus E_c(x)) = 1 - \frac{|E_c(x)|}{|E(x)|}, \quad (6)$$

where $E_c(x)$ denotes the set of entry locations with at least one charger in range of point x . We are going to use the probability of the opposite event in our measure, i.e., an EV is dispatched to an entry location having a minimum of one charger.

Continuous Measure. Within the modeling framework of these assumptions, we can then define our continuous measure of route electrification or coverage as

$$\text{Coverage}_r = \mathbb{P}(r \text{ is traversable}) \int_{x \in r} f(\mathbb{P}(\min_{i \in I(x)} N_i = 0), \mathbb{P}(v \text{ assigned to } e \in E_c(x))). \quad (7)$$

Empirical Implementation. Only routes that both start and end in a given state are included. We assume that the mean vehicle range follows a normal distribution as given by $b_{ec} \sim N(100, 10)$ or $b_{ec} \sim N(50, 50)$. The ‘entry location’ dataset used for clustering is filtered to only keep points within 0.5 miles of a route. Entry locations are composed of the highway exit/rest areas and all SafeGraph POIs. These ‘entry locations’ are then clustered using MiniBatchKMeans with $K = 1200$. The database of fast (or Level 3) charging stations from AFDC is restricted to those within 0.5 miles of a route and are assigned to entry location clusters. We assume a common vehicle arrival rate $\lambda = 0.1$ using an arrival point grid of 1 point per mile on routes. This is equivalent to an expected number of arrivals of 1 vehicle per 10 miles. Then, for each route-standard-month, we have the locations of each entry location cluster and the number of connectors at each cluster, which allows us to calculate the continuous measure as specified above.

Preliminary Results. Figures 14–16 present the different terms from Equation (7) we use to calculate the continuous measure (shown in Figure 17) for each fast charging standard in Califor-

nia and in Illinois using the charging station database from AFDC between November 2021 and December 2022. Figure 14 shows the average probability of a route being traversable, assuming a mean electric range b of 50 miles or 100 miles. First, the comparison across the three fast charging standards in Subfigure (a) shows that Tesla’s network does not serve well EVs with shorter ranges in California. On the other hand, the other two standards (Combo and Chademo) serve very well cars with short ranges with average probabilities of traversability being close to 0.9. For longer ranges, Tesla’s network performs a lot better though still slightly below the other two standards. Tesla’s own EV models are all long-range cars with 200 to 400-mile ranges and these findings are consistent with Tesla’s network being primarily designed to serve these long-range models. For the Combo and Chademo charging standards, under the modeling assumptions outlined above, Subfigures (a) and (b) indicate that the average probability of traversability is close to 1 at both shorter and longer ranges. In comparison, the average probability of a route being traversable is much lower in Illinois across all three standards for both longer and shorter mean vehicle ranges.

Figure 14: Average probability of a route being traversable (2021/11-2022/12)

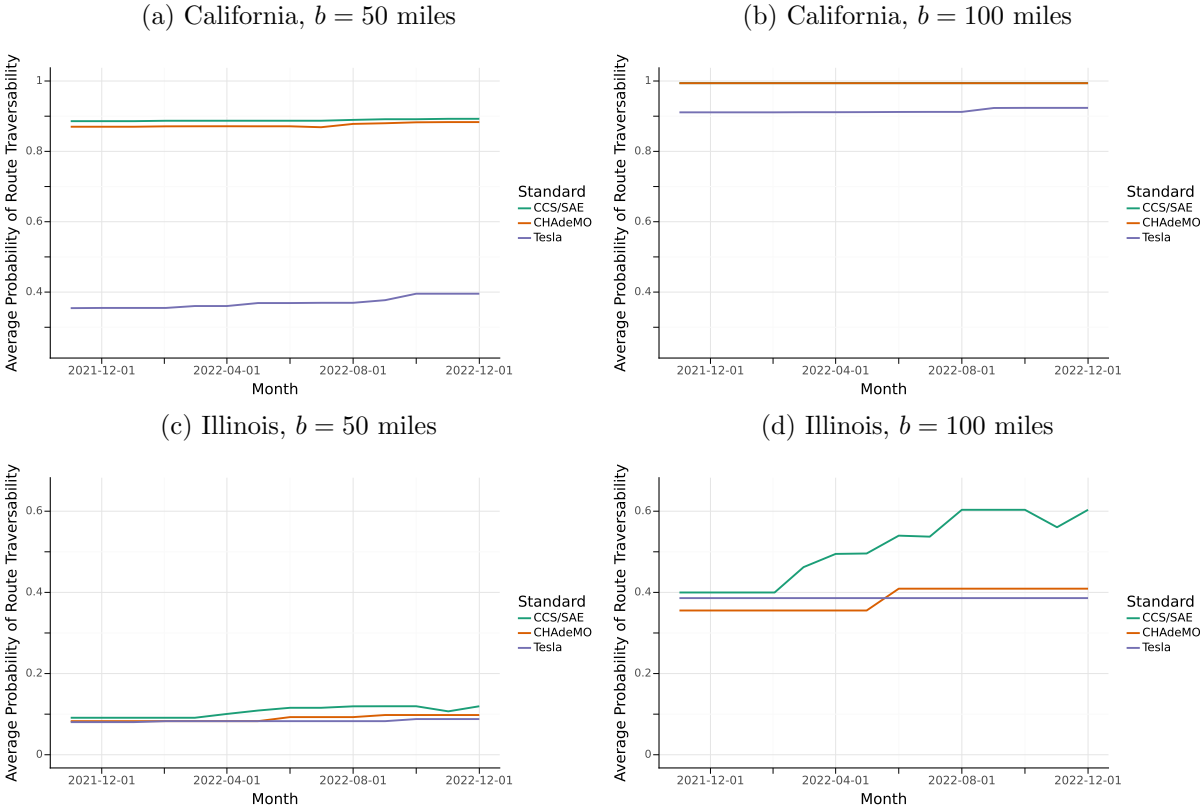


Figure 15 shows the average probability of a charger being available. Note that these results are calculated for an assumed vehicle arrival rate. In particular, we assume a common arrival rate

$\lambda = 0.1$ using an arrival point grid of 1 point per mile on the route.³ Therefore, instead of analyzing the levels of these probabilities, we focus on the changes observed over time, the differences across charging standards, and the differences across geographic areas (which are the states of California and Illinois in this case). Thus, our interpretation of the findings from Figure is that, for a fixed level of demand, they are driven by the changes in spatial allocations of stations across standards, across geographic areas, and over time. In all subfigures, the Combo standard serves vehicles the best. The figures together show that in both California and in Illinois, the average probability of a charger being available along a route improved over time for all three charging standards and for both shorter and longer vehicle ranges. The figures also indicate that for the same fixed level of demand, the average probability of charging availability is much higher in California than in Illinois.

Figure 15: Average probability of a charger being available (2021/11-2022/12)

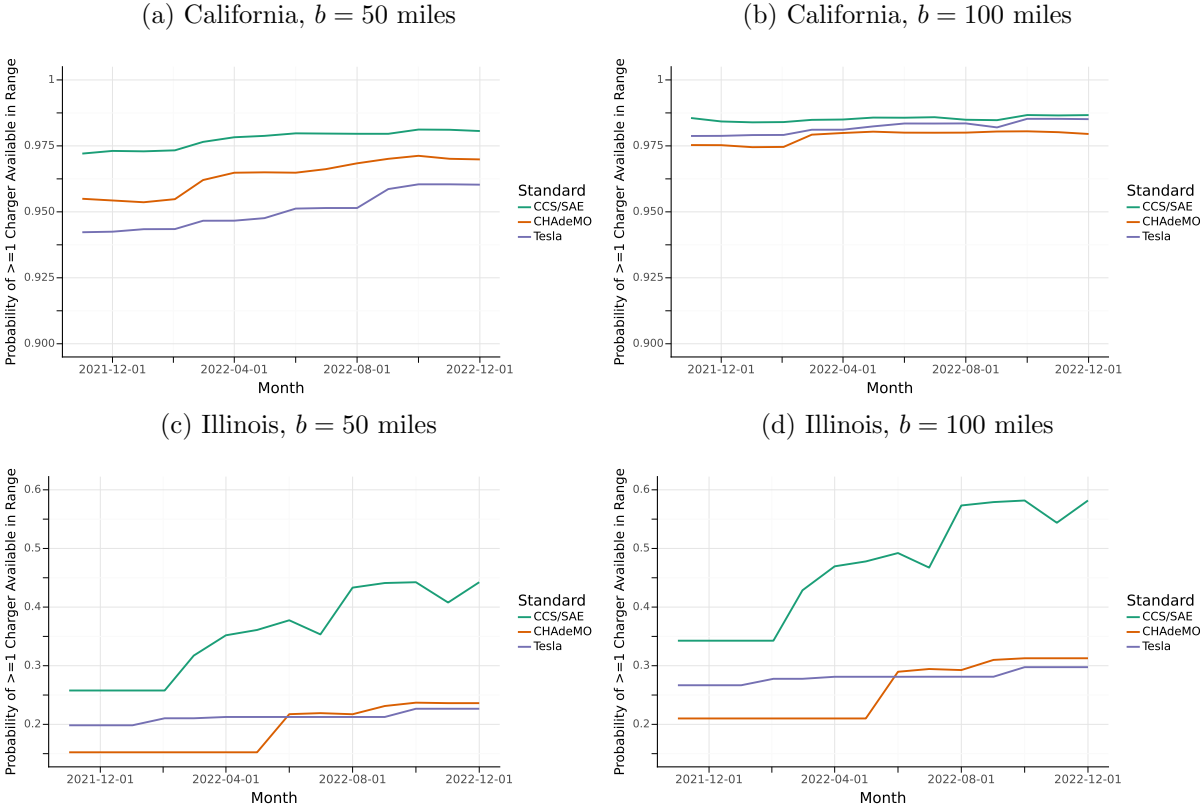
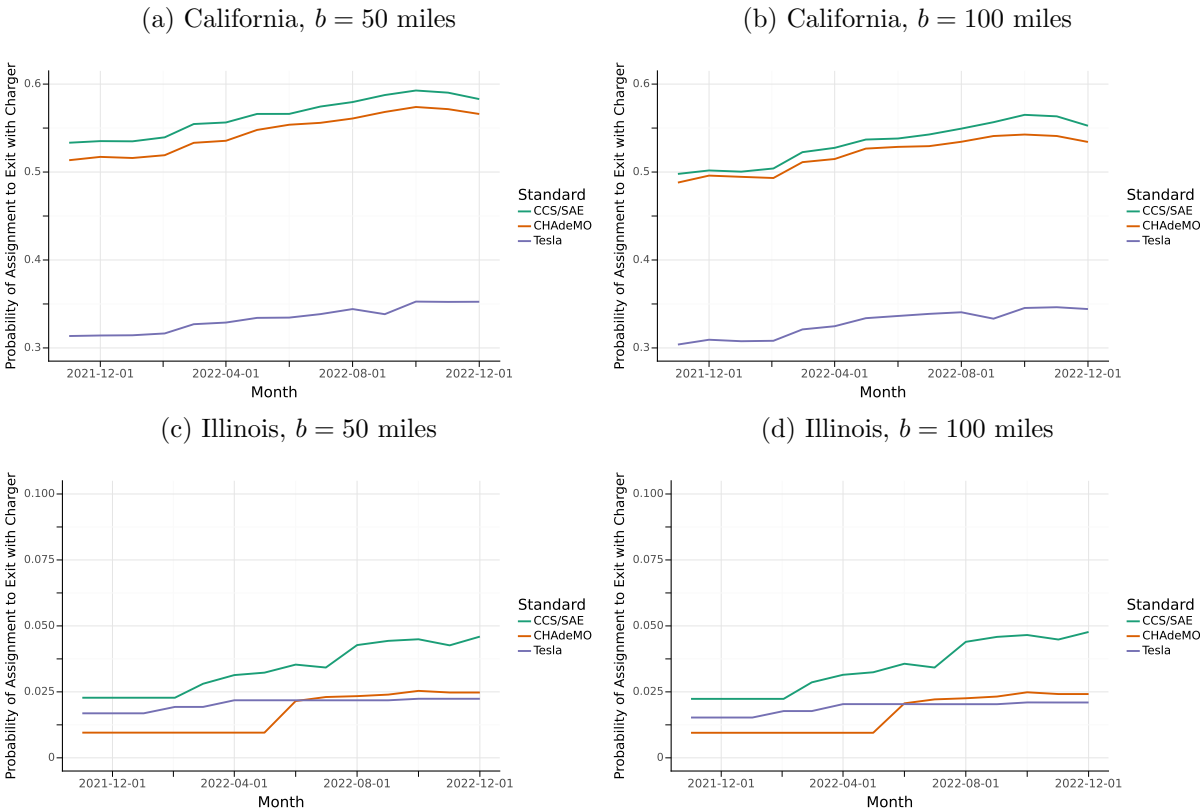


Figure 16 shows the average probability of an EV driver being assigned to an entry location with at least one charger. These figures reveal an interesting difference across charging standard in California. In particular, Tesla stations seem to be placed in denser areas with more highway exits

³Replacing the assumed λ with an empirically-based arrival rate by route is currently work in progress.

and rest areas. Thus, they cover significantly less of the available exits along a route. However, Tesla also puts more chargers at each location. Thus, we can observe a high probability for whether chargers are available as we saw in Figure 15, while noting a low probability for a car being dispatched to an exit (or rest area) with a charger for the Tesla network. The figures together suggest that the probability of being assigned to a highway exit or rest area with a charger increased over time for all three standards, for both shorter and longer vehicle ranges and in both California and Illinois.

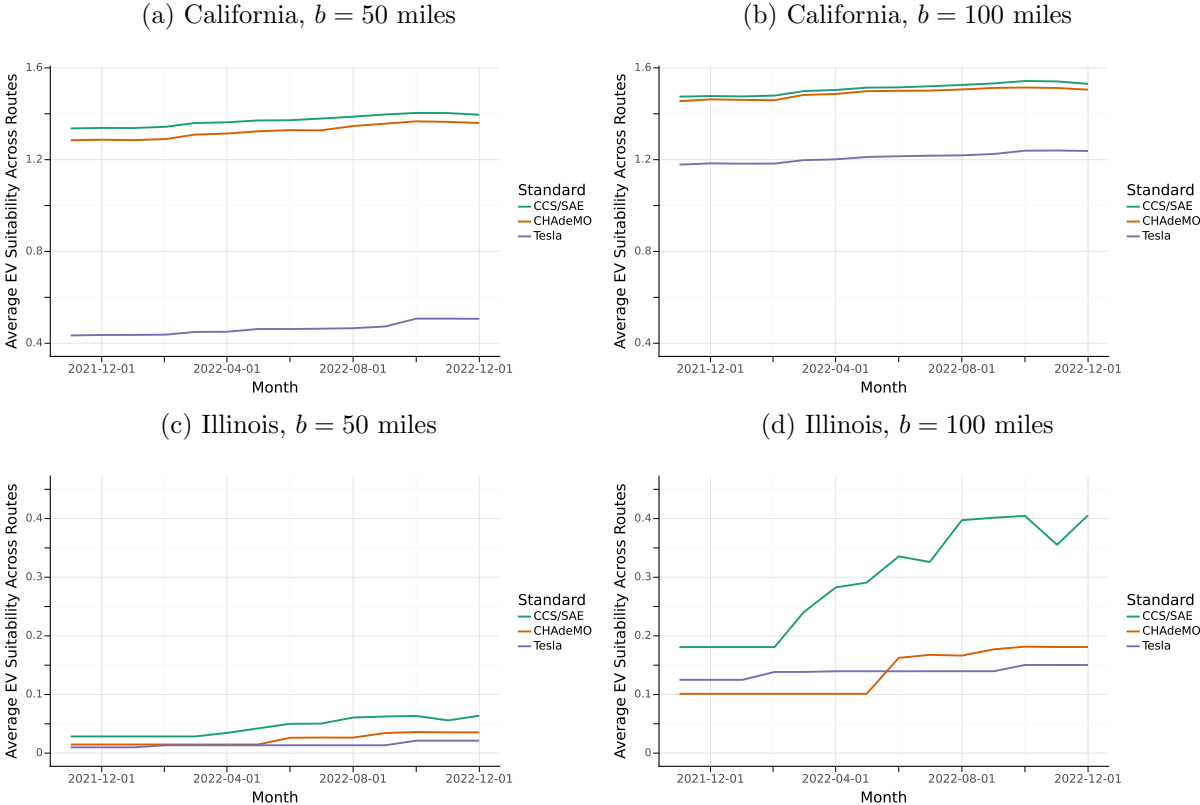
Figure 16: Average probability of EVs dispatched to an entry location with a charger (2021/11-2022/12)



Using Equation 7, we can calculate our continuous measure expressing EV suitability of routes across the three different fast charging standards and compare it to a policy counterfactual guided by the IIJA implementation plan for fast charging infrastructure. In particular, 2 chargers built every 50 miles on a 300-mile route with average vehicle range $b = 100$ miles yields a continuous measure value from 1.152 to 1.334. Figure 17 shows the continuous measure we computed. Under the conditions of our modeling framework, the calculated continuous measure values in California exceed the policy counterfactual values for the Combo and Chademo standards at both longer

and shorter mean vehicle ranges. In comparison, all three standards fare much worse in Illinois, regardless of the vehicle range considered.

Figure 17: Continuous measure (2021/11-2022/12)



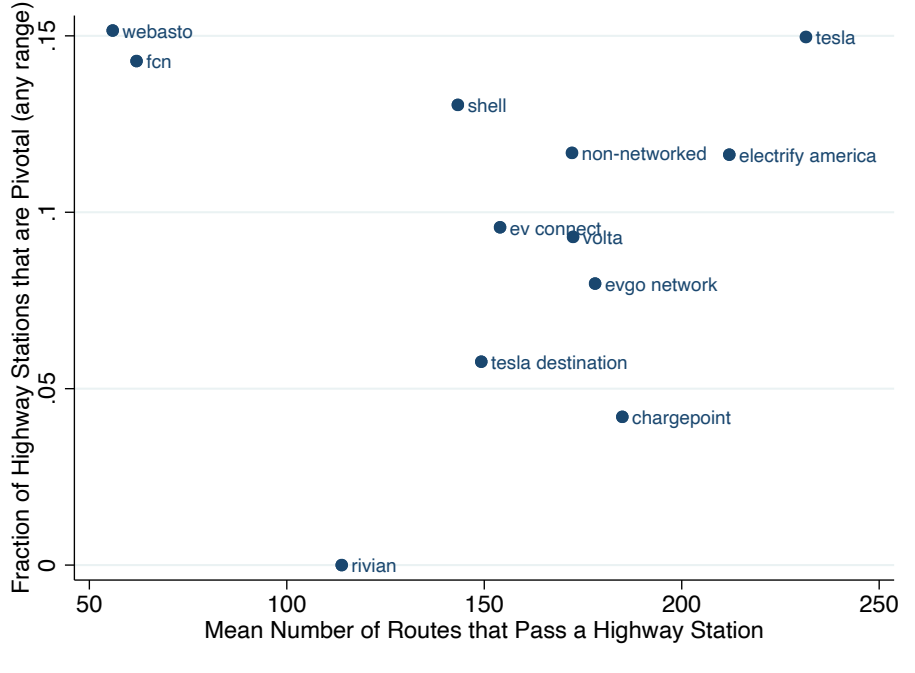
5 Site and Network Entry Motives

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.

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

Figure 18: Network vs. Site Entry Motives Averaged by Network; All Ranges



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 *betweenness 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.

Figures 18 and 19 plot 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). Figure 18 averages over all EV ranges, and Subfigures (a) and (b) of Figure 19 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.

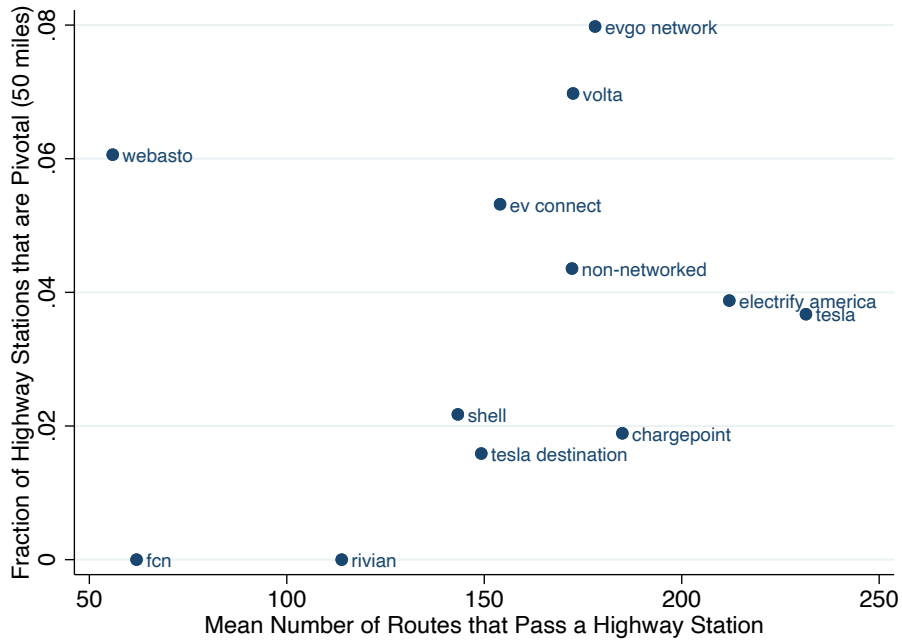
Figure 18 indicates Tesla and Electrify America appear to be trying to maximize the number

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.

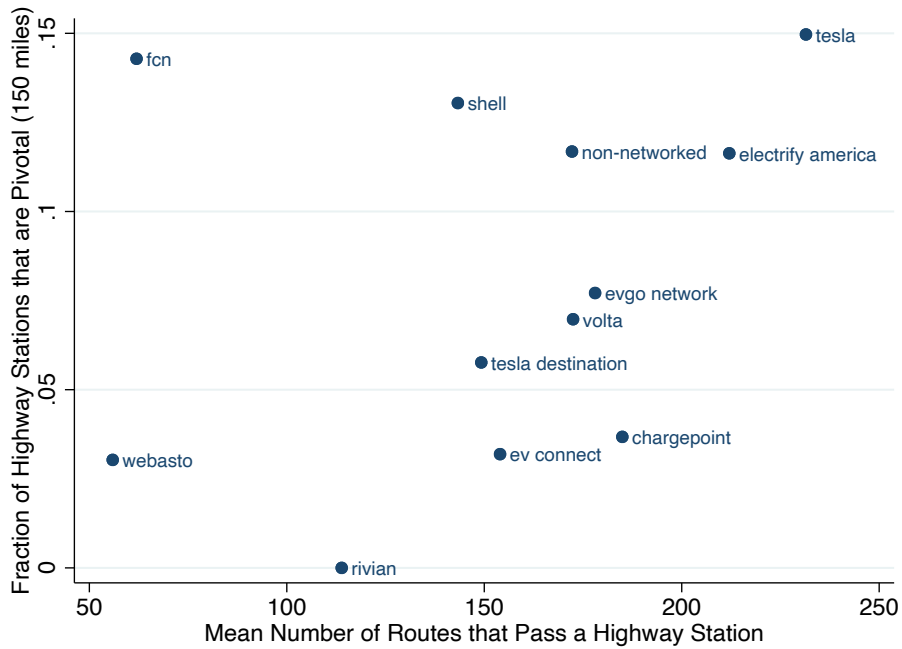
Figure 19 suggests that networks seem to specialize in serving EVs with different electric ranges. For example, eVgo stations have high network contributions at the 50-mile range, while Tesla and Electrify America stations have high network contributions at the 150-mile range. This analysis shows that 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.

Figure 19: Network vs. Site Entry Motives Averaged by Network; Different Ranges

(a) 50 miles



(b) 150 miles



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.

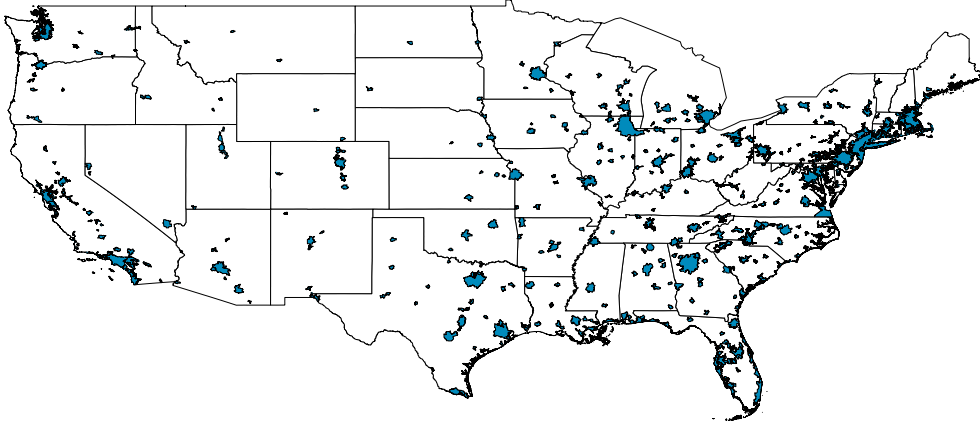
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Online Appendix

Appendix Figure 1: Map of FHWA Adjusted Urban Areas



Notes: This map shows where the 493 Adjusted Urban Areas, as defined by the FHWA, are located in the U.S., using data from the FHWA.

Appendix Table 1: Charger Types and Speeds; AFDC

	c		
	Level 1	Level 2	Level 3
Connector Type	J1772 connector	J1772 connector	Combo connector Chademo connector Tesla connector
Voltage	120 V AC	208 - 240 V AC	400 - 1000 V DC
Typical Power Output	1 kW	7 - 19 kW	50 - 350 kW
Estimated PHEV Charge Time from Empty 8-kWh Battery	5 - 6 hours	1 - 2 hours	N/A
Estimated BEV Charge Time from Empty 60-kWh Battery	40 - 50 hours	4 - 10 hours	20 minutes - 1 hour
Estimated Electric Range per Hour of Charging	2 - 5 miles	10 - 20 miles	180 - 240 miles

Notes: This table provides an overview of chargers for EVs. The table is adapted from the U.S. Department of Energy's Alternative Fuels Data Center. See https://afdc.energy.gov/fuels/electricity_infrastructure.html for more detail.

Appendix Table 2: 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: This table shows the distribution of vehicle trips by trip distance (in miles), obtained from the 2017 National Household Travel Survey (NHTS). Vehicle trips are defined as trips by a single privately-operated vehicle, regardless of the number of people traveling in the vehicle.

Appendix Table 3: 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: This table shows the distribution of vehicle trips by travel purpose, obtained from the 2017 National Household Travel Survey (NHTS). Vehicle trips are defined as trips by a single privately-operated vehicle, regardless of the number of people traveling in the vehicle.

Appendix Table 4: Number of Households by Household Vehicle Count; 2017 NHTS

Count of Households 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: This table shows the distribution of households by the number of vehicles owned by households, obtained from the 2017 National Household Travel Survey (NHTS). The 2017 NHTS weights its household data based on control totals found in the American Community Survey (ACS).

Appendix Table 5: 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: This table shows the distribution of vehicle trips by transportation mode, obtained from the 2017 National Household Travel Survey (NHTS). A person trip is defined as a trip from one address to another by one person using any mode of transportation.