Compatibility and Investment in the U.S. Electric Vehicle Market*

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August 2, 2023

Abstract

Competing standards often proliferate in the early stages of product markets and may lead to socially inefficient investment. This paper studies the effect of unifying three incompatible standards for charging electric vehicles in the U.S. from 2011 to 2015. I develop and estimate a structural model of vehicle demand and charging network investment to quantify the impact of a uniform charging standard. Variation in federal and state subsidies identify the demand elasticities. Counterfactual simulations show moving to a uniform charging standard increases consumer surplus by $400 million; car manufacturers build 5.8% more charging stations and sell 4.3% more electric vehicles.

*I thank my PhD advisors Christopher Knittel, Robin Lee, Ariel Pakes, James Stock, and Elie Tamer for their guidance and support. I thank Meghan Busse, Joseph Doyle, Evan Herrnstadt, Gaston Illanes, Sarah Jacobson, Divya Kirti, Shanjun Li, Charles Murry, Daniel Pollmann, Mar Reguant, Frank Schilbach, Robert Stavins, Che-Lin Su, Richard Sweeney, Thomas Wollmann, Matthew Zaragoza-Watkins, Michael Whinston, Yufei Zhao, and Fanyin Zheng for valuable comments. I thank John Smart and Sera White at the Idaho National Laboratory for information on U.S. federal electric vehicle programs. Data purchased for this research is generously supported by the Laboratory for Economic Applications and Policy. I gratefully acknowledge that this material is based upon work supported by the National Science Foundation Graduate Research Fellowship under Grant No. DGE1144152.

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1 Introduction

When firms invest in incompatible complementary goods or technical standards, should the government intervene and mandate compatibility? This question arises in a wide range of industries, from digital markets to manufacturing. Mandating compatibility has ambiguous welfare implications. A shift toward compatibility gives consumers access to the combined investments of all firms, which may benefit consumers by increasing variety, convenience, or other measures of quality. However, firms may reduce their investments, which would erode consumer benefits from compatibility. Compatibility turns firms' investments from substitutes that steal business from rivals to complements that have positive spillovers onto other firms. Therefore, firms may invest too much under incompatibility because private gains from business stealing do not contribute to social surplus, and they may invest too little under compatibility because private incentives do not internalize the positive spillovers. The theory literature shows that private incentives to provide compatibility can be either too high or too low relative to social incentives. The welfare effect of a compatibility policy is open to empirical analysis.

This paper empirically assesses the effect of compatibility on market outcomes and welfare in the U.S. electric vehicle market, which grew ten-fold in the number of models and annual unit sales from 2011 to 2015. Electric vehicles attract billions of dollars in government support for their potential environmental benefits and innovation spillovers. As with any alternative fuel transportation technology, such as hydrogen and natural gas, electric vehicles require refueling infrastructure for wider consumer acceptance. Manufacturers of electric vehicles have invested heavily in building fast charging stations to refuel electric vehicles. During the study period, car manufacturers coalesced around three mutually incompatible standards for fast charging. Incompatibility across different charging standards is an increasingly focal policy issue as governments continue to devote public funds to electric vehicle charging station infrastructure. For example, initial guidance and rules for the disbursement of funds under the bipartisan infrastructure law, the Infrastructure Investment and Jobs Act (IIJA) of 2021 explicitly discusses the qualifying charging standard.[1]

I evaluate the effect of a counterfactual compatibility policy in three main steps. First, I develop a structural model of consumer vehicle purchase behavior and car manufacturer build-out of charging networks. Second, I estimate the model using data from the U.S. electric vehicle market from 2011 to 2015. Third, I use the model and parameter estimates to simulate charging station

[1] https://www.fhwa.dot.gov/environment/alternative_fuel_corridors/nominations/90d_nevi_formula_program_guidance.pdf

investment, electric vehicle sales, and consumer surplus when all car manufacturers adhere to a single standard for recharging electric vehicles. I compare the status quo to the counterfactual market equilibrium and the social planner solution.

The mobility of drivers poses a challenge to specifying the relevant charging stations for an individual consumer. The most useful refueling stations to a consumer may be those that are near their driving paths and destinations rather than their home addresses (Houde, 2012). I cast the available charging network as a vehicle characteristic in the static, discrete-choice framework of Berry et al. (1995). The model captures three measures of charging network quality: the number of stations in a consumer's local market, the number of destinations that consumers can reach using a vehicle and stations that it can access, and the growth rate of the network with each standard.

I estimate the key parameters of my model using data on market-level vehicle sales and the number and locations of charging stations. I estimate an empirical Bayes posterior mean for market shares to reduce noise and eliminate zero market shares. To identify the endogenous demand parameters on price and charging stations, I collect an original panel dataset of federal and state government incentives for vehicle purchases and charging station investments. Government tax credits and rebates incentivize consumers to purchase electric vehicles and businesses to install charging stations. Conditional on market and time fixed effects, within-market changes over time in government subsidies are plausibly exogenous cost shifters due to idiosyncrasies in policy-making timing. Additionally, a portion of the charging stations in the dataset were built as part of a program in the American Recovery and Reinvestment Act of 2009 (Recovery Act) that chose recipient cities before electric vehicles became available for sale. Charging stations take time to complete due to permitting and construction. Conditional on market and time fixed effects, exact station completion times are plausibly exogenous to unobserved product characteristics and contemporaneous local demand conditions.

I model car manufacturers as competing in static oligopoly; they sell electric vehicles and build charging stations to support electric vehicle sales. In the model, firms search over charging station counts and geographic placement to maximize static profits. The specification of charging quality in the demand system helps to simplify the firms' charging station optimization problem. Equilibrium in each period is found with iterated best response. Combining demand parameter estimates and the first-order conditions of the profit function, I recover firms' markups for vehicles and costs for charging stations, which I find to be in line with engineer and industry estimates.

Using parameter estimates from the consumer and firm models, I assess the impact of a counterfactual policy that mandates compatibility in charging stations. I find that consumer surplus improves by $400 million over the 2011 to 2015 period, and firms build 5.8% *more* charging stations. The net effect of compatible charging stations and changes in charging station investment results in 4.3% more electric vehicles sold. Compatibility changes firms' investment incentives in two ways. First, firms have diminished business-stealing motives, which reduces their charging station investments. Second, charging stations become strategic *complements*, which could increase investments. The net effect of these two forces depends on empirical demand and cost parameters, and I find that firms' investments increase. However, firms do not fully internalize or appropriate their benefits on consumer surplus and other firms, and the social planner would build 2% more charging stations. The gains from compatibility are not symmetric. Firms that produce longer-range electric vehicles benefit more from compatibility than firms with lower-range vehicles.

This paper contributes to three strands in the literature. First, this paper contributes to the empirical understanding of the impacts of compatibility. Theoretical predictions of gains from compatibility are ambiguous, as firms' private incentives to achieve compatibility may be either higher or lower than social incentives (Katz and Shapiro, 1985, 1986). Previous empirical work on the impact of compatibility has found considerable gains in consumer welfare (Ho, 2006) and producer efficiency (Gross, 2020). However, firms' strategic responses to compatibility may moderate the gains in consumer welfare (Ishii (2007), Lee (2013), Knittel and Stango (2008, 2011)). Ferrari et al. (2010) model ATM investment by banks and usage by consumers, and find that coordinated investment by firms leads to substantially lower investment than socially optimal. In this paper, firms make individual investment decisions even in the compatible stations counterfactual. After computing the counterfactual equilibrium charging network built by firms, I find that compatibility in charging standards improves consumer surplus despite firms decreasing the number of charging stations that they build. Compatibility does not fully erode firms' incentives to invest in complementary goods for their products when their products remain differentiated.

Second, this paper contributes to the growing literature on endogenous product positioning by endogenizing charging station investment by car manufacturers. When product varieties are discrete, firms' product choices can be thought of as entry decisions. A line of literature recovers fixed costs of new product entry to compute welfare or solve for new product introductions (Wollmann (2018), Eizenberg (2014), Nosko (2014), Sweeting (2013), and Draganska et al. (2009)). In settings such as the charging network investment problem in this paper, firms face a continuous choice space. Crawford et al. (2019) and Fan (2013) study the size of cable bundles and newspaper content quality, respectively.

Third, a rapidly growing literature investigates different features of the electric vehicle market. Holland et al. (2016, 2019), Graff Zivin et al. (2014), and Michalek et al. (2011) evaluate the environmental benefits of electric vehicles in the short run. They find high geographic variation in the environmental benefits of electrifying transportation within the U.S., depending on the fuel mix of electricity production and population density. More recent work by Holland et al. (2022) and Gillingham et al. (2021) has investigated emissions impacts in the longer run when consumer charging behavior and grid investments can be optimized. A second strand of this literature focuses on the design and impacts of subsidies for EVs and other green technologies (Clinton and Steinberg (2019), Sheldon et al. (2017), Borenstein and Davis (2015), Holtsmark and Skonhoft (2014)). This work finds that consumers respond to subsidies in their decisions to adopt electric vehicles and other green technologies. Third, using a two-sided market framework, Li et al. (2017) and Springel (2021) find that car purchases and charging station build-out respond positively to each other and that subsidizing charging station entry is more cost-effective in increasing electric vehicle sales.[2] Fourth, Remmy (2023) and Sinyashin (2021) study the policy implications of endogenizing firms' choices in the electric range attribute. This paper differs from prior work on electric vehicles by using existing subsidies as identifying variation in a structural model to evaluate a counterfactual policy about charging standard compatibility. It is the first to model and empirically evaluate car manufacturer investments in charging stations.

The rest of this paper is organized as follows. Section 2 discusses the growth of the electric vehicle market and relevant technical details about charging stations and standards. Section 3 describes the data and government subsidy policies for vehicles and charging stations. Section 4 specifies a model of consumer vehicle choice and car manufacturer investment in charging stations. Section 5 discusses the empirical Bayes estimator for market shares, identification, and estimation results. Section 6 uses the model and estimates to simulate market outcomes under a compatibility policy. Section 7 concludes.

[2] Greaker and Heggedal (2010) and Pavan (2015) study positive feedback loops between vehicle demand and refueling infrastructure for hydrogen fuel cell and natural gas cars, respectively.

2 The U.S. Electric Vehicle Industry

2.1 Growth of the U.S. electric vehicle market

Electric vehicles (EVs) are an increasingly important segment of the U.S. automotive industry, which as a whole accounts for more than 3% of U.S. GDP (U.S. Bureau of Economic Analysis). EVs can be classified into two types: (i) battery electric vehicles (BEVs), which only run on electricity, and (ii) plug-in hybrid electric vehicles (PHEVs), which can take gasoline as a backup fuel source. The unifying feature across BEVs and PHEVs is that they can be plugged in for recharging, in contrast with conventional hybrids which cannot be plugged in for recharging. For example, Toyota first launched the Prius as a conventional hybrid in 2000, and in 2012 added a plug-in hybrid version.

Tesla Motors unveiled the first modern-day EV at a press event in 2006, a luxury sports car called the Roadster and priced at more than $100,000. Since late 2010, automakers have introduced more affordable and mass-market options that span a wide range of prices and features.[3] The three available models in 2011 collectively sold about 14,000 units in U.S. metropolitan statistical areas (MSAs). From 2011 to 2015, the number of models available and annual units sold both grew about ten-fold, to 27 available models and about 140,000 units (Table 1). Although the number of EV models has increased over time, Table 1 shows that the means, minimums, and maximums of product characteristics such as manufacturer suggested retail price (MSRP) and electric range have not changed much during this period. Appendix Figure A1 plots the distribution of MSRP, manufacturer discounts, and electric range by year. The number of publicly-accessible charging stations for electric vehicles also grew ten-fold, from 2,000 by the end of 2011 to 20,000 by the end of 2015.

Electric range and charging infrastructure are as important for EVs as fuel tanks and gas stations are for gasoline cars. Electric range, the distance that an EV can travel starting with a fully charged battery, generally increases with the size of the battery. Electric range also depends on other factors, such as weight, aerodynamics, and any other factors that contribute to fuel efficiency. Charging infrastructure relies on the electric grid's generation, transmission, and distribution assets. This paper focuses on the equipment that allows EVs to connect to the grid. An EV can recharge from any ordinary electrical outlet, which is the slowest option. However, drivers may occasionally

[3] Technology for EVs has existed since the 1800s, but gasoline became the dominant fuel by the 1920s. A confluence of advances in battery technology and tightening environmental regulation has led to a revival of the EV market in recent years. See U.S. Department of Energy (2014) for a detailed historical account.

need faster charging options away from home, such as on a busy day of running errands or during a long-distance trip. This paper focuses on charging infrastructure away from drivers' homes.

EV charging speeds fall into three tiers. Faster charging equipment delivers electricity at higher rates but costs more upfront to install. Level 1 is the ordinary wall outlet used by most other consumer electronic devices. Level 1 charging may also be referred to as "trickle-charging" and adds 2 to 5 miles per hour. Level 2 charging stations can fully charge an electric vehicle in four to six hours, so they are suitable for destinations where drivers may park for a while. In residential homes, they can be attached to the same type of outlet used by laundry dryers and electric ovens. Many employers and retail establishments, such as shopping malls, restaurants, and hotels, have installed Level 2 charging stations as an amenity for their employees and customers.

The fastest charging option is called Level 3 or fast charging. Most Level 3 charging stations, especially in the U.S., use direct current. These charging stations work in conjunction with a transformer (from alternating current to direct current) to deliver high-powered electricity. A 30-minute session can recharge an EV by 80% on average. Level 3 charging stations tend to be installed where drivers need a nearly-full recharge in a short time, such as at highway rest stops. They require the highest fixed costs because of the transformer and higher permitting, legal, and electrician labor costs. Not all EV models are capable of Level 3 charging, because the battery packs and other onboard systems must be designed to accommodate the high-powered direct-current electricity.

2.2 Charging standards and compatibility policy

In the U.S. market during the 2011 to 2015 period studied in this paper, car manufacturers designed their EVs around three different standards for Level 3 charging, each not compatible, or interoperable, with the others. In contrast, Level 1 and 2 charging use uniform standards across all vehicle brands. A charging standard has two parts: (i) a set of electronic communication protocols between the vehicle and the charging station, and (ii) a physical connector. Figure 1(a) depicts the connector shape of each Level 3 charging standard and lists corresponding car manufacturers with their fast-charge-capable EV models offered from 2011 to 2015. The charging standard for each firm is the same within the U.S. across all local markets. Car manufacturers without vehicle models next to them in Figure 1(a) had not yet produced fast-charge-capable EVs by the end of 2015 but had announced that future models would follow a certain standard. Charging standard coalitions seem to reflect global regional groupings. There may be idiosyncratic factors and hysteresis in which firms join which coalition. This paper focuses on firms' charging station investments, taking their charging standard choice as given. Over time, some car manufacturers have changed standards alliances. For example, Kia moved from Chademo to the Combo standard in 2018. A growing number of major automakers including GM, Ford, Rivian, Volvo, and Mercedes-Benz announced in 2023 that they would join the Tesla standard in the coming few years. I discuss how the paper relates to the recent shift toward the Tesla standard and the economics questions raised by these firms' decisions in the conclusion.

Figure 1(b) shows where EV models lie in "characteristics space" of MSRP and electric range. Symbols denote EVs by Level 3 charging standard. Tesla offers relatively higher electric range at higher prices. The point furthest to the right, with the highest electric range during this period, is the Tesla Roadster, but it is marked as "Other BEV" because the first-generation Roadster was not compatible with the Tesla Supercharger network. PHEVs as a group have lower electric range, which may be acceptable to consumers because of their backup gasoline engines. PHEVs and BEVs span a similar price range.

Automakers have been involved in building Level 3 charging infrastructure throughout the U.S.[4] Figure 2 plots the number of charging stations with each standard over time, with the y-axis on a log scale. Figure 2 shows that charging stations for each standard are first built around the launch of their first fast-charge-capable EV. Nissan, in partnership with the Tokyo Electric Power Company and other Japanese automakers, developed the Chademo charging standard in 2010, at the same time as the development and release of the Nissan Leaf. Tesla Motors announced in September 2012 that it would build a Supercharger network to blanket the U.S., three months after the first delivery of the Tesla Model S. Meanwhile, other car manufacturers, working through the Society of Automotive Engineers (SAE), released the specifications of the SAE J1772 Combo[5] standard in October 2012. However, no cars were marketed under the Combo standard until BMW released the i3 in May 2014. Two months later, BMW announced that it would support the build-out of charging stations under the Combo standard.[6] Figure 2 also shows from the slope of each curve that the growth of each network is quite fast initially and slows over time. Electric range of vehicles offered by Nissan and BMW are similar during this period, so Nissan's much larger network may

[4]The reason for low third-party entry in Level 3 charging remains an important question for future research. One plausible explanation is that the size of the electric vehicle fleet does not provide enough revenue relative to the fixed costs of building a charging station.

[5]The common standard for Level 2 uses a J1772 connector. The SAE Combo standard for Level 3 adds two DC pins under the J1772 port, hence the name "Combo." See Figure 1 for depictions of Level 3 connectors.

[6]Tesla builds and operates a vertically-integrated charging network, while other manufacturers contract with third-party networks. The vertical integration decision is an interesting topic for future research. This paper focuses on network size and location choices. Rivian's Adventure Network is a more recent example of a vertically-integrated charging network by a vehicle manufacturer.

be due to its earlier start.

Figure 3 shows locations of charging stations by standard in September 2015. Tesla charging stations trace out routes between cities, including cities far apart from each other. Chademo and Combo stations tend to be located within or near cities. These differences in location choice are consistent with the differences in electric range across standards shown in Figure 1(b). Each standard has presence throughout the country.

Incompatibility in fast-charging standards is a potential barrier to EV adoption and may be socially inefficient. Any given EV can only access a subset of the fast-charging infrastructure, and any fast-charging station can only serve a subset of EV drivers. Incompatibility may suppress growth on either side of the market relative to an interoperable fast-charging infrastructure. Compatibility or interoperability can be achieved in two different ways. One path toward compatibility is to pick a "winner." The European Union Parliament requires that all stations built after 2018 must at least be compatible with their chosen standard. In other words, multiple standards are allowed at each station via connectors or adapters (European Commission (2014)), as long as Parliament's chosen standard is also available.[7] Another way to achieve compatibility is via adapters. With three different charging standards, any given vehicle would need two adapters. Six one-way adapters would be required in total. This paper abstracts away from the transition path and examines the difference between the status quo and a counterfactual U.S. EV market that started with only one fast charging standard. Consumers are modeled to be indifferent to the technical specifications of a charging standard and only value a charging standard for the size and locations of its network.

3 Data and Descriptive Evidence

3.1 Data

Market-level information on consumer demand for new cars comes from vehicle registration data, compiled by IHS Automotive (now S&P Global Mobility and formerly R.L.Polk) from each state's department of motor vehicles. The dataset reports the number of registrations for each electric vehicle (BEV and PHEV) model, geographic market, and quarter. Each vehicle model is defined as a brand, model name, model year, and fuel type. There are 30 EV models offered by 20 car brands from 2011 to 2015; niche models that only sold a handful of units such as the McLaren P1 for over $1 million are dropped from the analysis. Geographic markets are delineated by Metropolitan

[7] See Ferwerda et al. (2018) for details on the evolution of charging standards in Europe.

Statistical Areas (MSAs). The panel includes 359 MSAs and 20 quarters from 2011 to 2015. Vehicle registration data are merged with model-level characteristics information from MSN Auto, the Environmental Protection Agency, and *Automotive News*, including manufacturer-suggested retail price (MSRP), manufacturer discounts, battery capacity, and electric range. I assign vehicle characteristics associated with the base trim for the modal model year reflected in unit sales.

Charging station data are published by the Alternative Fuels Data Center (AFDC) of the Department of Energy. The AFDC maintains one of the most comprehensive databases on charging stations in the U.S. and includes opening date, location (street address and GPS coordinates), speed tier (Level 1, 2, or 3), standard for Level 3 charging, and operator. I define a charging station as a collection of charging posts at the same address and affiliated with the same operator. For example, charging posts near every entrance of a mall, if all operated by ChargePoint, comprise one charging station. Charging posts operated by Tesla in the parking lot of the same mall would comprise a second charging station. A charging post plugs into an EV via a connector. The charging standard of a station is identified by the types of connectors present. The other component of a charging standard, the communication protocol, is embedded in the charging post's software.

Nearly all EV charging stations are hosted in the parking area of some other establishment, such as a parking garage or a mall parking lot. In an analogy to gas stations, a single charging post can be compared to a single gasoline pump. A charging station is a collection of posts as a gas station is a collection of pumps. One difference is that gas stations nearly always have their own street address while charging stations are referenced by the address where the charging posts are installed.

The American Community Survey provides information on commuting flows. I collect data on U.S. federal and state subsidies for constructing instruments. The next subsection describes the variation in federal and state subsidies for EVs and charging stations.

3.2 Descriptive evidence of the impacts of subsidies

EVs face two main barriers to higher market shares: they are more expensive than comparable gasoline cars, and they lack adequate recharging infrastructure. The empirical analysis in this paper uses two types of government subsidies in the U.S. to identify parameters in the structural model, one for EV purchases and another for charging stations. This subsection describes the policies, demonstrates independent variation in the subsidies for the two sides of the market, and presents the strength of the impact of the subsidies on their targets.

Consumers in the U.S. can receive subsidies from the federal and state governments to help offset the purchase price of an EV. The U.S. federal income tax credit for EV purchases is a piecewise-linear function of battery capacity and ranges from \$2500 to \$7500 for qualifying EVs. Federal EV subsidies phase out for each manufacturer after sales exceed a cap. No manufacturer reached their sales cap during the study period. Some state governments offer subsidies in addition to the federal incentives, ranging from \$250 to \$7500. Each state's EV subsidy may change over time and may depend on vehicle characteristics such as battery capacity or fuel type (PHEV vs. BEV).

EV charging stations also receive federal and state government support. The American Recovery and Reinvestment Act of 2009 (ARRA) allotted funds to the Department of Energy for vehicle electrification initiatives, of which \$115 million were spent on projects related to EV charging infrastructure.[8] The ARRA stations were completed from 2010 to 2013 and were allocated to different cities across the U.S. In addition to the ARRA, some state governments subsidize charging stations as a percentage of upfront hardware and installation costs.

Subsidy variation. Figure 4 demonstrates independent variation in state subsidies for EVs and charging stations. Panel (a) presents a scatterplot of state EV subsidies (which vary by state, quarter, and vehicle model) against the maximum state charging station subsidy for any charging level (which varies by state and quarter and could be further disaggregated by Levels 2 and 3). State charging station subsidies range from 0 to 80%, with many states offering 0, 50, or 80%. Within these subsidy levels, there remains variation in state EV subsidies ranging from \$0 to over \$5000. There is also considerable variation across MSAs and over time in ARRA-subsidized charging stations (Panel (b)). For example, at \$1500 of state EV subsidies, the number of ARRA stations ranges from 0 to more than 200. The observations with a \$1500 state EV subsidy include 50 MSAs in 5 states; out of these, 26 MSAs in 4 states receive a positive number of ARRA stations during the study period. The city with more than 200 ARRA stations is Los Angeles.

The empirical analysis later in the paper uses within-MSA variation across vehicles and over time. Panel (c) presents a scatterplot of state EV and charging station subsidies relative to their state means. The demeaned subsidies show a great deal of independent variation. For example, where charging station subsidies are 10 percentage points higher relative to the mean, demeaned EV subsidies range from -\$1700 to \$4300. Panel (d) presents a scatterplot of state EV subsidies and ARRA-funded station arrivals relative to their state means. Again, there is considerable

[8] The ARRA projects involving EV charging are called The EV Project and the ChargePoint America Project.

variation in ARRA stations within each EV subsidy level and vice versa. Appendix Figure A2 presents variation in EV and charging station subsidies aggregated to the state-year level. While aggregation smooths over some of the variation, Figure A2 still shows that EVs are subsidized at times and places different from charging stations. Figure 4 more closely matches the empirical specification in the rest of the paper, which uses within-MSA variation across vehicles and over time.

Relationship between subsidies and intended targets. Figure 5 presents the empirical relationship between subsidies and their targets.[9] Panel (a) plots means of log EV sales at the market-quarter-vehicle model level as a function of the state EV subsidy using a binned scatterplot, controlling for market and quarter FE and observable vehicle characteristics such as electric range and BEV indicator.[10] The line of best fit is generated from an OLS regression of log EV sales on EV subsidies with the same set of control variables, and the reported standard error is clustered at the market-vehicle model level.[11] The estimate of the slope is .022, which implies that a one standard deviation increase in state EV subsidies ($1300) is associated with a 2.8% increase in unit sales for a given EV model in a given market and quarter, on average. In comparison, unit sales of EVs in the U.S. at the market and model level grew at an average quarterly rate of 5.6% from 2011 to 2015. Alternative specifications yield qualitatively similar results, such as the association between the log of total EV sales to subsidies averaged over EV models by state and quarter. The structural analysis in the paper models consumer vehicle choice and substitution patterns across vehicle models explicitly.

Panels (b) and (c) of Figure 5 examine the relationship between new Level 2 or 3 charging stations and subsidies for them using binned scatterplots. Panel (b) plots the mean log number of new charging stations as a function of the maximum available charging station subsidy in a state and quarter, controlling for state and quarter fixed effects. The line of best fit is generated from an OLS regression of the log number of new charging stations on the maximum state charging

[9] The analysis requires instruments for both EV sales and new charging stations. The EV and charging-station subsidies provide independent variation to carry out the analysis. When the three instruments are included in the first-stage regressions, the coefficients on the instruments are similar to the main estimates (see Appendix Table A2): in the model for log(EV sales), state EV subsidy has a coefficient of 0.019 (s.e. = 0.010); in the model for log(New Charging Stations), the coefficient on state charging station subsidy is unchanged at 0.009 (s.e. = 0.002), and in the model of New Charging Stations, the coefficient on new ARRA stations has a coefficient of 0.559 (s.e. = 0.193).

[10] Appendix Figure A3 presents alternative specifications using different levels of aggregation, at the state-quarter-vehicle model level for panel (a) and MSA-quarter level for panels (b) and (c), with qualitatively similar results.

[11] I cluster standard errors at the market-vehicle model level because EV subsidies may depend on vehicle characteristics such as battery capacity or fuel type (PHEV vs. BEV).

station subsidies for any charging level, controlling for state and quarter fixed effects. The reported standard error is clustered at the state level. The slope of the line of best fit is .009, which implies that a one standard deviation increase in state charging station subsidies (16.8 percentage points) is associated with a 15.8% increase in new stations in a given state and quarter, on average. Given an average of 17 new stations in each state and quarter from 2011 to 2015, this corresponds to an additional 2.7 stations in each state and quarter.

Panel (c) of Figure 5 plots the mean number of new charging stations as a function of the number of newly arriving ARRA stations in a state and quarter, controlling for state and quarter fixed effects. The line of best fit is generated from an OLS regression of the number of new charging stations on the number of newly arriving ARRA stations, with the same fixed effects. The reported standard error is clustered at the state level. The estimated slope of the line of best fit is .56, which implies that an additional ARRA charging station arriving in a state and quarter is associated with .56 additional charging stations on net in that state and quarter. The slope is less than 1, which suggests that ARRA stations crowd out some other investments.

4 Model

This section presents a model of the EV market that captures the role of charging networks in consumers' vehicle choices. Car manufacturers play a series of static two-stage games. At the beginning of each period, the last period's charging station investments arrive, any new vehicle models from an exogenous R&D process become available, and unobserved vehicle quality, demand, and cost shocks become public information. In the first stage, firms invest in charging stations that arrive at the beginning of the next period. In the second stage, firms set prices, and consumers choose a vehicle based on price and quality, including the charging network of each vehicle.

4.1 Consumer demand

Consumer vehicle demand follows the discrete-choice framework of Berry et al. (1995) and Petrin (2002). In each period t and market m, consumers arrive to purchase a vehicle. Consumer i's conditional indirect utility from choosing an EV j depends on the consumer's attributes and vehicle characteristics. It is given by:

$$U_{ijmt} = \delta_{jmt} + \mu_{ijmt} + \varepsilon_{ijmt},$$

where δ_{jmt} is the mean utility common to all consumers within a market and period, and μ_{ijmt} is the mean-zero individual deviation from mean utility. Consumer-vehicle-specific taste shocks, ε_{ijmt}, are assumed to be i.i.d. Type-I extreme value distributed. The outside option is choosing a non-EV, with its indirect utility normalized to $U_{i0mt} = \varepsilon_{i0mt}$. The mean utility δ_{jmt} of vehicle j is:

$$\delta_{jmt} = \alpha p_{jmt} + q_{jmt}\gamma + x_{jmt}\beta + \xi_{jmt},$$

where p_{jmt} is the price, q_{jmt} is a vector of charging network quality measures, and x_{jmt} is a vector of other vehicle characteristics and control variables. Unobserved vehicle-specific attributes and demand shocks are represented by ξ_{jmt}. Individual deviation μ_{ijmt} from mean utility is given by:

$$\mu_{ijmt} = \sigma_p p_{jmt}\nu_{ip} + \sum_k \sigma_k q^k_{jmt}\nu_{ik},$$

where ν_{ip} and ν_{ik} are standard normal draws. I include random coefficients on vehicle price, local charging network size, and the number of other markets that are reachable. The charging network quality measures are described in detail below. Consumer i chooses vehicle j if $U_{ijmt} \geq U_{ij'mt}$ for all j'. The market share for vehicle j comes from integrating over individual choices:

$$S_{jmt} = \int \frac{exp(\delta_{jmt} + \mu_{ij})}{\sum_{j'} exp(\delta_{j'} + \mu_{ij'})} \mathrm{d}\nu_i.$$

The parameters from the demand model to be estimated are $\theta = (\alpha, \beta, \gamma, \sigma)$. The unobserved ξ_{jmt} can be inferred from the model as a function of parameters θ. I assume that ξ_{jmt} evolves according to a first-order autoregressive process,

$$\eta_{jmt}(\theta) = \xi_{jmt}(\theta) - \rho\xi_{jm,t-1}(\theta),$$

and that η_{jmt} are mean-zero and independent across products j, markets m, and time periods t.

Charging network quality. Consumers consider three aspects of charging network quality, $q_{jmt} = (\log(L_{smt}), D_{jmt}, g_{st})$, where s is the Level 3 charging standard of vehicle j. First, local trips are supported by Level 2 and 3 charging stations within a consumer's home market, $\log(L_{smt})$. All EVs on the same standard can access the same local stations, so L has subscript s rather than j. I define L_{smt} as a weighted sum of Level 2 and 3 charging stations in a market, with weights equal to the proportion of the market (MSA) population that commute by car *to* the county that contains each charging station. Besides private or dedicated charging at home, drivers tend to charge at retail establishments or work (Idaho National Laboratory (2015)).[12] The log functional form accommodates decreasing marginal utility, which is consistent with surveys that find most drivers conduct their away-from-home charging at a few stations.[13] Appendix Figure A4 shows variation in the number of local charging stations, L_{smt} over markets and time, by standard.

Second, inter-city stations allow consumers to reach some destinations D_{jmt} from each market m with vehicle j. Appendix Figure A5 shows variation in the number of MSA destinations, D_{jmt}, over markets and time, by standard. D_{jmt} is written with subscript j to highlight that the usefulness of the inter-city stations depends on a vehicle's electric range. Figure 1(b) shows that from 2011 to 2015, EVs within each standard have similar electric ranges. Thus, in the status quo of Figure A5, the number of destinations does not vary within each standard. However, in the counterfactual with a single charging standard, lower-range EVs do not necessarily have the same number of destinations as higher-range EVs.

Third, the current growth rate g_{st} in the nationwide total number of charging stations represents a measure of future charging network quality for each standard s. A well-established network can attract customers based on its existing stations, while a new network without many existing stations may be able to signal a large future network with a high current growth rate. In Figure 2, each network begins with a high growth rate, as shown by the initially steep slope. A higher growth rate is predictive of a larger network (level of each curve) in the future, conditional on the current size. The network growth rate incorporates some considerations of a forward-looking consumer in an otherwise static framework. Compared to a completely myopic consumer, a consumer with network growth rate in the utility function may choose an inside good (EV) earlier and may also choose among the inside goods differently.

Vehicles without fast-charging capability can only use Level 2 stations in their local network, reach MSAs within range of the battery, and experience zero network growth rate. PHEVs are assigned charging network quality based on their battery range, fast-charge capability, and charging standard. The mobility offered by the internal combustion aspect of PHEVs is constant and absorbed by a fuel type indicator variable. In estimation, I interact the local and inter-city network terms, $\log(L_{smt})$ and D_{jmt} with a fuel type indicator variable to allow consumers to value charging network quality differently for PHEVs and BEVs.

[12] See Hardman et al. (2018) for a review of how consumers use EV charging infrastructure.

[13] A micro-founded model with consumers who each only use up to some number of most preferred stations can be consistent with the log functional form if consumers have heterogeneous and smoothly distributed across physical space or taste space.

Price. Consumers pay a purchase price p_{jmt}, which is equal to MSRP less manufacturer discounts (MD) and government subsidies:

$$p_{jmt} = \text{MSRP}_{jt} - \text{MD}_{jt} - \text{State Subsidy}_{jmt} - \text{Federal Subsidy}_{j}. \tag{1}$$

MSRP and manufacturer discounts are the same across all markets and only vary across vehicle models and time. State subsidies vary across vehicle models, markets, and time. Federal subsidies vary across vehicle models but do not vary across time during the data period of this study. This definition of purchase price assumes full pass-through of subsidies, which is supported by and can be consistent with prior results from the literature (Muehlegger and Rapson (2022), Sallee (2011), Busse et al. (2006)). Instrumental variables help to identify the price coefficient. The identifying assumption is that the instruments are uncorrelated with unobservables, such as measurement error from not observing the transacted price. Section 5.2 discusses the pass-through results from the literature, the construction of the instruments, and the identification arguments.

Other demand model considerations. Vehicle characteristics besides price and charging network quality are assumed to evolve according to an exogenous product development process. Blonigen et al. (2017) show that 70% of vehicle models are redesigned every 4 to 7 years, and an entirely new model takes even longer to design and develop. The electric fuel segment is consistent with the overall industry pattern. For example, the earliest electric vehicle models from the 2011 model year only received major updates in late 2016.

One limitation of the model is that the outside good does not include the option value of waiting to choose in the future. The option value of waiting may be limited in this case because consumers would have to wait many years, until at least 2017 for significantly longer battery range at lower prices, such as the Chevrolet Bolt, 2018 model-year Nissan Leaf, and the Tesla Model 3.[14] Later-arriving charging stations are accessible to earlier buyers of the same charging standard. For consumers who wait, Gowrisankaran and Rysman (2012) show that a static choice model would bias the estimated demand coefficients toward zero, because people who are waiting for the prices and characteristics to stabilize would be wrongly modeled as not responding to the changing prices or characteristics of the existing options. The net effect of any bias in demand estimates on welfare results is theoretically ambiguous, because bias in charging network coefficients and the

[14]Tesla offered reservations for the Model 3 for $1,000, which was an option to purchase the Model 3 at some approximate priority in the production queue. The reservation signals interest but is fully refundable and not a commitment to purchase.

price coefficient have opposite effects on welfare.

I do not explicitly model the consumer costs of charging station usage for three reasons. First, non-pecuniary costs of using charging stations - such as search, travel, and hassle costs - are reflected in the preference parameters on the included charging network quality measures. Second, Level 3 stations, the focus of this paper, are often free to use for the life of the car (Tesla) or the first few years after purchase (Nissan and BMW) during the study period. Third, charging station utilization data would be required but are not publicly available.[15]

4.2 Car manufacturer investment

The model endogenizes firm choices in the quantity and locations of charging stations, conditional on the standards coalitions that they have joined. These two control variables are part of a dynamic optimization problem which may include firms' expectations beyond the time coverage of available data. Therefore, the model of firm choices is static. I assume that conditional on the choice of standard and the charging stations that have already been installed, the static profit function is proportional to the dynamic value function, so that optimization from the static model is consistent with a long-run dynamic game.[16]

Firms may produce multiple EV models. The variable profit π_{ft} of firm f in period t from its EV offerings $j \in \mathscr{J}_{ft}$ is the sum over markups from cars sold, given by

$$\pi_{ft}(\boldsymbol{q}, \boldsymbol{p}) = \sum_{m} \sum_{j \in \mathscr{J}_{ft}} \left[p_{jt} - mc_{jt} + ZEV_{jmt}\right] S_{jmt}(\boldsymbol{q}, \boldsymbol{p}) N_{mt},$$

where mc_{jt} denotes the marginal cost of producing car j in t, and N_{mt} is the size of market m in period t. ZEV_{jmt} denotes the shadow value of credits that a vehicle can earn in states with a Zero-Emission Vehicle (ZEV) Mandate.[17] Market shares S_{jmt} are functions of charging network quality $\boldsymbol{q}$ and vehicle prices $\boldsymbol{p}$ as well as the exogenous characteristics, shocks, and demand parameters. Firms maximizing profits over EVs can be consistent with EV divisions being tasked with growing

[15] The physical incompatibility between vehicles and charging equipment on different standards could be conceptualized as an infinite price for accessing a different standard. Differential access prices between 0 and infinity would likely temper the impacts of a compatibility policy found in this paper.

[16] The static model can generate increasing EV demand over time from an increasing stock of charging stations and any decreases in EV prices.

[17] ZEV mandates are imposed on car manufacturers of a certain size and are present in ten states, including California. I use \$5,000 as the shadow value of each ZEV credit, which is the regulatory fine that firms pay for failing to meet ZEV sales obligations. McConnell et al. (2019) describe the ZEV mandate in detail and calculate that Tesla sold credits at \$2400 per credit in 2015. The estimates and results of this paper are robust to assuming a \$2400 shadow value for each ZEV credit.

their segment.[18]

Firms set one price nationally for each model j and period t, which is the MSRP minus manufacturer discounts. The firm's price p_{jt} does not include government subsidies that are contained in the consumer-facing price p_{jmt} of Equation 1. Assuming Nash Bertrand competition in prices, I back out markups and marginal costs from the first-order conditions of the variable profit function. Let $\Delta(\boldsymbol{q},\boldsymbol{p})$ be a matrix whose element $\Delta_{jh} = -\frac{\partial S_h(\boldsymbol{q},\boldsymbol{p})}{\partial p_j}$ if j and h are sold by the same firm and zero otherwise. The first-order condition of the firms' pricing problem implies the following vector of vehicle marginal costs:

$$\boldsymbol{mc} = \boldsymbol{p} + (\Delta(\boldsymbol{q},\boldsymbol{p}))^{-1}\boldsymbol{s} \tag{2}$$

where $\boldsymbol{s}$ is the vector of products' market shares, and $\odot$ is the element-by-element matrix multiplication operator. The markup is given by $\Delta(\boldsymbol{q},\boldsymbol{p}))^{-1}\boldsymbol{s}$.

I model the charging network build-out problem of the major player for each Level 3 charging standard: Tesla, Nissan (Chademo), and BMW (Combo).[19] In each period, firms simultaneously choose charging network investment of size A_{ft} to improve the next period's charging network quality $q_{f,t+1}$. The marginal cost of A_{ft} is given by:

$$c'(A_{ft}) = \kappa_1 + \kappa_2 A_{ft} + \omega_{ft}, \tag{3}$$

where ω_{ft} is a period-and-firm-specific cost shock, assumed to be i.i.d. The profit from new charging stations depends on how they are allocated across M local networks and the national inter-city network, $a_{ft} = (l3_{f1t}, \ldots, l3_{fmt}, \ldots, l3_{fMt}, n_{ft})$. The elements of allocation vector a_{ft} sum up to $A_{ft} = n_{ft} + \sum_m l3_{fmt}$. The potential locations for charging stations can be ordered by marginal profit, detailed below, so that marginal profit is decreasing in A_{ft}. Firms choose A^*_{ft} such that

$$\pi(A^*_{ft}) - \pi(A^*_{ft} - 1) \geq c'(A^*_{ft}); \quad \pi(A^*_{ft} + 1) - \pi(A^*_{ft}) \leq c'(A^*_{ft} + 1), \tag{4}$$

where for clarity of exposition, I write $\pi(A)$ in place of $\pi(q(A), p(A))$.

Within the static framework, the model allows firms to incorporate revenue considerations beyond the next quarter. Vehicle demand responds to the stock of all charging stations available, so a firm's investment in the current period helps the firm sell more cars in each subsequent period. Inequality 4 contains one-period comparisons of profits and costs of capital. They are equivalent to

[18] The organizational economics literature has studied when decentralized decision-making is optimal for multi-product firms with asymmetric product divisions (Rantakari (2008) and Roberts and Saloner (2012)).

[19] By the end of 2015, other firms had not built nor advertised involvement in building charging stations besides at their car dealerships.

firms considering a discounted sum of future profits which result from current-period investment. Both sides of the inequalities are scaled when summing to obtain a discounted net-present value, and optimal geographic placement is unchanged.

Charging station placement. A firm f builds A_{ft} charging stations in each period, with allocation $a_{ft} = (l3_{f1t} \ldots l3_{fmt} \ldots l3_{fMt}, n_{ft})$ across the M local markets and the single national network and $A_{ft} = |a_{ft}|$. The placement of charging stations improves each of the three charging network quality measures $q_{jmt} = (\log(L_{smt}), D_{jmt}, g_{st})$ as follows:

$$
\begin{aligned}
L_{smt} &= L_{sm,t-1} + \sum_{c \in m} w_c (l2_{mt} + l3_{fmt}), \\
D_{jmt} &= d_{jmt}(N_{s,t-1} + n_{ft}), \\
g_{st} &= \frac{A_{ft}}{G_{s,t-1}}.
\end{aligned}
$$

Firm f has Level 3 charging standard s. The total number of stations with standard s and period t is G_{st}, and $G_{st} = G_{s,t-1} + A_{ft}$. The network growth rate g_{st} is thus the investment size A_{ft} divided by the size of the network in the previous period. The inter-city portion of the network in period t has N_{st} stations, and $N_{st} = N_{s,t-1} + n_{ft}$. The function d_{jmt} maps the inter-city network size to the number of destinations D_{jmt} that vehicle j can travel to, which also depends on j's battery range. I describe $d(\cdot)$ in more detail below. The local network L_{smt} of market m grows from exogenous arrival of Level 2 stations $l2$, which are universally accessible, and the firm's investment $l3_{fmt}$. The w_c are commuting weights for each county c in market m.

I make four modeling choices to simplify the problem of optimally placing a given number of charging stations, two for the local networks and two for the national inter-city network. The demand model provides independence of local networks. An improvement in one market's local network does not impact consumer vehicle choice and profits in any other market. Local charging stations can thus be ordered in decreasing marginal profit, which is computationally fast. If the local networks were not independent, then the optimal solution can only be found by enumeration. With 359 markets (M) and 200 stations (A) to allocate across markets, there are $\binom{M+A-1}{M} \approx 2.62 \times 10^{156}$ possible allocations, which is more than the number of atoms in the observable universe. Within each local network, for estimating demand coefficients, I use the observed GPS coordinates of charging stations to assign them to counties and commuting weights w_c. For estimating charging station costs and counterfactual simulations, I abstract away from the choice over which county to put a station in and instead define a "geographic HHI" from the commuting weights, $geohhi = \sum_{c \in m} w_c^2$. If the entire population in a market commutes to a single county for work, then its geographic HHI would be 1. Every new station would go to that single county and receive full weight. If a market has the population commuting to all counties evenly, then its geographic HHI would be low. A new station in such a market, no matter where it is placed, can only serve a portion of the population.

For the national inter-city network, I model the firm's choice as whether to electrify the route between two cities. I assume that firms optimally space out their stations along the route and abstract away from choosing the exact set of GPS coordinates. The cost of connecting each pair of stations is estimated from the data. Even with the simplification in choosing which routes to electrify, the optimal network build-out problem is computationally intractable. For estimating charging station costs and counterfactual simulations, I use the ordering of route electrification observed in the data. When a firm allocates n_{ft} stations to the national inter-city network, function d_{jmt} adds the next set of routes from the observed ordering that cost up to n_{ft} and computes the number of destinations that each vehicle can reach from each market. For example, if the route between New York City and Washington DC was previously electrified, and the route from Boston to New York is added to the charging network, then Boston gains New York and Washington DC as destinations, while New York and Washington DC each gain Boston as a destination.

With the above modeling choices for the inter-city networks and the national network, the optimal placement of stations across local and national networks is computationally fast for a given partition of A_{ft} between local and national networks. The search over all partitions of A_{ft} between the local and national inter-city networks is linear in A_{ft} and computationally fast. For a given choice of A_{ft}, the network growth rate g_{st} is constant over all possible station allocations. Firms compare the marginal variable profit from the optimal allocation of A_{ft} with the marginal cost.

5 Estimation, Identification, and Results

In this section, I describe the identification and estimation of the demand and cost parameters. I eliminate observed zero market shares by shrinking the data toward an empirical Bayes prior formed from similar markets. This procedure pulls market shares away from zero and enables the estimation framework of Berry (1994) and Berry et al. (1995). Readers who are not interested in the technical details of the empirical Bayes procedure can skip directly to Subsection 5.2 for identification and Subsection 5.3 for estimation results.

5.1 Zero market shares

This paper studies the U.S. electric vehicle industry from its inception when zero units of some new car models were sold in some local markets and time periods. The zeros considered in this analysis are when products are known to be offered but not purchased; products that are not offered in a given market (for example, inferred from announced staggered roll-out schedules) are considered true zeros, and those product-market combinations are dropped from estimation. The dataset covers all new vehicle registrations for each market and period, so any observed zeros are not due to sampling error, such as from disaggregating a national sample or survey to the local level. As described in McFadden (1974) and Berry et al. (1995), each consumer's choice is an independent draw from a multinomial distribution with a set of purchase probabilities. The observed market share aggregates over the consumers' multinomial draws. However, even when the consumer sample is the full population, observed market shares may still be zero in practice due to small purchase probabilities coupled with finite market size. Table 2 shows that in the study period, 36.4% of market shares are 0 in any given model-market-quarter combination, ranging from 18.5% (2011) to 45.9% (2015). The number of zeros increases over time because new EV models arrive and car manufacturers expand the number of markets where EVs are offered.

The true purchase probabilities underlying the observed market shares are unknown. One common practice in demand estimation is to use the observed market shares in place of the true purchase probabilities, which is implicitly the maximum likelihood estimator (MLE). Zero market shares are censored at zero and therefore mask information about the true underlying purchase probabilities. They also make the inversion step impossible in the Berry (1994) and Berry et al. (1995) estimation framework. I instead use a parametric empirical Bayes or shrinkage estimator, which generates strictly positive posterior estimates of the true purchase probabilities from information in other markets. This is similar to the transformation in Gandhi et al. (2023). To preserve important heterogeneity across markets, each market's empirical Bayes prior is formed using similar markets. I define the set of similar markets to be the 50 markets closest in income per capita, or 14% of the 359 total number of markets. Table A4 in Appendix B investigates priors of different sizes and shows that demand estimates are robust to the choice of the number of cities in the empirical Bayes prior.

I model the quantities purchased of each vehicle in each market, K_{jm}, as a draw from a binomial distribution with N_m trials, or total vehicles purchased. The purchase probabilities are s^0_{jm}. The time subscripts t have been suppressed throughout this subsection for simplicity. The purchase probabilities s^0_{jm} are different for each vehicle and market and are drawn from a Beta prior distribution with hyperparameters λ_{1jm} and λ_{2jm}. This is a Beta-Binomial model of market shares (which can be generalized to a Dirichlet-Multinomial). The distributions of K and s are given by:

$$K_{jm} \sim \text{Binomial}(N_m, s^0_{jm}),$$
$$s^0_{jm} \sim \text{Beta}(\lambda_{1jm}, \lambda_{2jm}).$$

The posterior distribution of the purchase probability is also a Beta distribution,

$$s_{jm} \sim \text{Beta}(\lambda_{1jm} + K_{jm}, \lambda_{2jm} + N_m - K_{jm}),$$

with posterior mean given by,

$$\hat{s}_{jm} = \frac{\lambda_{1jm} + K_{jm}}{N_m + \lambda_{1jm} + \lambda_{2jm}}.$$

For reference, the observed shares (MLE) are,

$$\hat{s}^{MLE}_{jm} = \frac{K_{jm}}{N_m}.$$

I use strictly positive posterior means, $\hat{s}_{jm}$, in demand estimation rather than the MLE. In large markets, the empirical Bayes posterior is very similar to the observed shares because the observed sales dominate the prior.

For each car j in market m, the Beta prior is formed using market shares from similar markets, $l \in \mathscr{P}_m$, where l is a market from the set of similar markets $\mathscr{P}_m$. The parameters of the Beta prior, λ_{1jm} and λ_{2jm}, are estimated from maximizing the log of the likelihood over the outcomes in the markets that form the priors,

$$f(K_{jl}, l \in \mathscr{P}_m | \lambda_{1jm}, \lambda_{2jm}) = \prod_{l \in \mathscr{P}_m} \binom{K_{jl}}{N_l} \frac{\Gamma(\lambda_{1jm} + \lambda_{2jm})\Gamma(\lambda_{1jm} + K_{jl})\Gamma(N_l - K_{jl} + \lambda_{2jm})}{\Gamma(\lambda_{1jm})\Gamma(\lambda_{2jm})\Gamma(N_l + \lambda_{1jm} + \lambda_{2jm})}.$$

I estimate a pair of hyperparameters $\hat{\lambda}_{1jm}$ and $\hat{\lambda}_{2jm}$ for each vehicle, market, and period. The posterior mean estimate of purchase probabilities is given by $\hat{s}_{jm} = \frac{\hat{\lambda}_{1jm} + K_{jm}}{N_m + \hat{\lambda}_{1jm} + \hat{\lambda}_{2jm}}$. The posterior estimates of market shares have lower variance and are strictly positive, as shown in the bottom panel of Table 2. The means of the observed and empirical Bayes posterior market shares are quite similar, .00083 and .00080, respectively. Posterior mean estimates of market shares range from 5.72e-12 to .00162. Figure A7 plots observed shares against their posterior mean estimates.

Berry et al. (2004) provide conditions on the number of consumers relative to the number of products for consistency and asymptotic normality of the demand estimates when using the MLE as purchase probabilities. I assume that the same conditions hold when using the empirical Bayes estimator. Appendix B discusses the advantages of the empirical Bayes estimator over other common methods and summarizes the methodological papers that treat zero market shares. Table A7 compares to demand estimates from aggregating to the annual level.

5.2 Identification

Firm investments in prices and charging stations in each period may be correlated with unobserved product characteristics. Instruments and moment conditions used in estimation are described below. I maintain the standard assumption that other product characteristics besides price and charging network are exogenous. Market and time fixed effects are included for all specifications.[20] The instruments vary within market, over time, and across vehicle models. Market fixed effects control for local factors that do not vary much from 2011 to 2015, such as local inclinations to be green, the proportion of housing stock with off-street parking (thus enabling at-home charging), the types of electrical wiring in the housing stock, and quality of public transit. Time fixed effects control for national factors that do not vary across markets, such as national macroeconomic trends and global fuel price shocks.

Identifying price coefficients. I define a vector of instrumental variables, Z^{price} from government subsidies and BLP instruments. The identifying assumption is that Z^{price} is orthogonal to unobserved characteristics $\xi(\theta)$,

$$\mathbb{E}[Z^{price}\xi(\theta)] = 0. \tag{5}$$

The first two sets of instruments are federal and state subsidies. Prices that consumers pay also include time-varying manufacturer discounts, so federal and state subsidies are not the sole sources of price variation. The third set of price instruments, the sum of characteristics of other firms' products in the market (BLP instruments), are relevant because they affect the markups that firms can charge. The BLP instruments are uncorrelated with ξ_{jmt} under the assumption that the other product characteristics arrive as part of an exogenous development process.

Federal EV subsidies vary by vehicle model and are determined by a piece-wise linear function

[20] Results are imprecise and have unstable signs if brand or product fixed effects are included. The instruments constructed from government subsidies vary across markets and time; the specification with only market and time fixed effects is preferred because it allows variation across competitors to identify the model.

of battery capacity. This instrument provides identification from the functional form of federal EV subsidies, which is uncorrelated with unobservables ξ_{jmt} conditional on battery capacity. The structure of these EV subsidies was determined in 2009. I also assume that firms do not choose components of ξ_{jmt} based on the subsidy functional form.

State EV subsidies vary by state, vehicle model, and over time. With market and time fixed effects, the identifying assumption is that changes in state subsidies over time and differences in subsidies across states or car models within states are uncorrelated with unobservables ξ_{jmt}. Idiosyncratic differences in state legislative processes support the identifying assumption that the timing of subsidy changes is plausibly random. Laws may become effective immediately, in the next tax or calendar year beginning in January, or the next fiscal year beginning in July. The structure of state subsidies is also plausibly exogenous after controlling for characteristics that these subsidies condition on, such as battery capacity. Figure A6 shows the variation in state EV subsidies over vehicle models, states, and time.

The definition of price in Equation 1 assumes that consumers receive the full amount of discounts and subsidies. We may be concerned that car manufacturers or dealers set prices in a way that leads to incomplete pass-through. There are several reasons to expect high pass-through of EV subsidies and discounts. First, car manufacturers set prices and discounts nationally, so they are unlikely to adjust prices in places and times where states adjust EV subsidies. Second, car manufacturers also try to discipline car dealer pricing, such as through inventory offerings, as described in Sallee (2011). Third, consumer awareness of EV subsidies is high because they are well-publicized via car manufacturer websites, consumer guides, and car dealers. Busse et al. (2006) hypothesize that pass-through increases with consumer awareness of the discount. Recent evidence finds high pass-through of subsidies for alternative fuel vehicles. Sallee (2011) finds that consumers capture the full federal and state incentives for the conventional hybrid car, the Toyota Prius. Muehlegger and Rapson (2022) analyze an EV subsidy program for low- and middle-income buyers in California and find results consistent with full pass-through.

We may still be concerned that car dealers adjust prices systematically to capture subsidies.[21] I am not aware of a dataset that could quantify subsidy pass-through at the local market level, which would require transacted vehicle prices and quantities across many cities, ideally with national

[21] I have run the counterfactuals with price elasticities 10% higher and lower than the estimated elasticities. Charging station investment correspondingly shifts by up to 10% higher or lower, respectively, though the qualitative takeaways of compatibility improving social welfare and the gains being larger for longer-range EVs are robust to the alternative price elasticities.

coverage. The empirical analysis includes market and time fixed effects, which control for time-invariant and market-invariant factors that can lead to incomplete pass-through, such as car dealer market structure or local marginal costs.[22] EV price instruments constructed from state subsidies that vary across states, vehicle models, and time are arguably uncorrelated with car dealer market power.

Identifying coefficients for charging network quality. I construct instrumental variables from state charging station subsidies and lagged charging network quality. Section 3.2 shows independent variation in vehicle and charging station subsidies.

First, state subsidies for charging stations are cost shifters that are assumed to be uncorrelated with demand shocks conditional on market and time fixed effects. Second, ARRA-funded stations arrive over time, as described in Section 3.2. Recipient cities are chosen before the beginning of the U.S. EV market. Each recipient city receives stations predetermined by program funding availability, independent of the realized evolution of the EV market in each city. Regulators may have chosen recipient cities where they expected the highest growth rates in or marginal impacts on local electric vehicle adoption. However, the exact timing of stations arriving in each recipient city could be due to idiosyncratic permitting and construction lags that are plausibly uncorrelated with unobserved ξ_{jmt},

$$\mathbb{E}[Z^{chargingsubsidy}\xi(\theta)] = 0. \tag{6}$$

The third set of charging station instruments is the one-period lags of local charging network size and number of MSA destinations. The stations arriving at the beginning of period t are chosen by car manufacturers based on $\xi_{jm,t-1}$, before $\eta_{jm,t}$ are realized. Therefore, new stations arriving in period t are uncorrelated with $\eta_{jm,t}$. The identifying assumption is that $Z^{charging}$ is orthogonal to innovations in unobservables, $\eta(\theta)$,

$$\mathbb{E}[Z^{charginglag}\eta(\theta)] = 0. \tag{7}$$

Random-coefficient logit demand parameters θ are estimated using a GMM framework with moment conditions in Equations 5, 6, and 7.

Identifying charging station costs.

[22] See Goldberg and Hellerstein (2008) for a discussion of the determinants of incomplete pass-through.

5.3 Estimation Results

Table 3 reports demand estimates from the logit model (Columns 1 through 3) and the random-coefficient logit model (Column 4). Column 1 shows OLS logit results. Column 2 shows IV logit results with instruments as described in Subsection 5.2 and unobservables ξ in all moments. Column 3 uses innovations on unobservables, η, in the charging-station-related moments of Equation 7. Column 4 adds random coefficients on price, local network size, and number of MSA destinations. The estimated autocorrelation in unobservables, $\hat{\rho}$, in Columns 3 and 4 are nearly identical, at .78 and .77, respectively. The first-stage minimum eigenvalue statistic (Cragg-Donald Wald F-statistic), the analog to the first-stage F-statistic for multiple endogenous regressors, is 266.37, indicating strong instruments (Stock and Yogo (2005)).

The estimated coefficients across all specifications are positive for network growth rate, battery range, engine power, and all-wheel drive. The coefficient for the BEV indicator variable is negative, which suggests that BEVs are less preferred than PHEVs during the study period from 2011 to 2015. Given the vehicle models offered during this time, consumers prefer having gasoline as an additional fuel source.

I conduct three sensibility checks on the estimates in Table 3 Column 4. First, the price coefficients translate to a median price elasticity of 3.42, which is in line with prior literature (Berry (1994), Berry et al. (1995), and Goldberg (1995)).[23] Second, the coefficient for battery capacity, though statistically imprecise, implies an average willingness to pay of \$140 per kWh. This is close to \$100, which industry analysts and experts consider as the point when EVs could become price-competitive with internal-combustion engine vehicles.[24] Third, the coefficients for charging network quality imply a willingness to pay for a Level 3 charging adapter. Chademo is the dominant and *de facto* single standard in Japan. Tesla developed a one-way adapter to give Tesla vehicles access to Chademo stations and in March 2015 launched the adapter in the U.S. market. Based on a conversation with a Tesla engineer, the adapter took at least two years of development. From the demand system and estimated demand coefficients, I find that willingness to pay for access to Chademo stations by Tesla vehicles is on average \$790 in 2015. Tesla initially launched

[23] Li et al. (2017) find a price elasticity of -1.29. I can replicate the estimates of Li et al. (2017) (I estimate a price elasticity of -1.25) by adopting their specification. The most important contributors to the differences in estimates are (1) their use of log sales quantities compared to the logit/r.c.-logit demand system here, and (2) their modeling vehicles with the same charging network quality while I restrict vehicles to access only the compatible charging stations. The choices in specifications suit the research question of each paper. My demand system allows me to recover substitution patterns for counterfactuals, and differences in charging standards are central to this paper's research question.

[24] https://www.bloomberg.com/news/newsletters/2021-05-25/hyperdrive-daily-the-ev-price-gap-narrows

the adapter for pre-order at $1000 and shortly after adjusted the retail price to $450. Willingness to pay for an adapter computed from the model is consistent with the observed retail prices.

PHEV and BEV indicator variables are interacted with local charging network size and number of MSA destinations to show whether consumers value charging networks differently by fuel type. Table 3 Columns (1) and (2) suggest that local charging network size is more important for PHEVs. The difference disappears in Columns (3) and (4) when using innovations on unobservables, η, in the moments for lagged charging stations. The coefficient for the number of MSA Destinations for PHEVs is negative due to consumer substitution. PHEVs and BEVs with the same charging standard can access the same set of charging stations. When the number of MSA destinations increases for a charging standard, consumers substitute away from PHEVs on that standard toward BEVs. The magnitude of the coefficient for the MSA destinations $\times$ PHEV interaction term appears large, but it matches the magnitude of the BEV indicator and thus could be sensible.

Marginal costs and markups of vehicles are computed following Equation 2. The estimated vehicle marginal costs range from $20,400 for the Mitsubishi i-MiEV to $113,800 for the BMW i8. Vehicle marginal cost estimates seem sensible when compared to industry estimates of the costs of batteries during the study period. I estimate a marginal cost of $24,100 for the Nissan Leaf (which has a 24kWh battery for the most basic trim) and $62,400 for the Tesla Model S (which has a 60kWh battery for the most basic trim). Battery packs cost between $1000 to $500 per kWh during this period and are the bulk of EV marginal costs. Table A3 presents estimates of own-price elasticities, markups, and vehicle marginal costs.

Per-period Level 3 charging station costs are inferred from vehicle sales profits following Inequality 4 and assuming that it binds with equality. A firm builds a station if it expects vehicle profits in each future period (assumed equal next-period profits) to exceed the per-period station cost. Cost parameters are estimated following Equation 3 and presented in Table 4. Instruments include the average (weighted by market size) state and ARRA charging station subsidies and the BLP instrument for the BEV fuel type. These instruments are shifters for charging station costs or charging station demand. Column (1) is the base specification with no additional controls, Column (2) includes a time trend, and Column (3) includes time fixed effects. The coefficient for new charging stations is positive across all specifications, implying increasing marginal costs. Increasing marginal costs could reflect constraints such as the managerial capacity of the department for charging network roll-out. The implied average per-period cost that a firm would be willing to pay for a charging station is reported in the bottom row in thousands of dollars. The estimate from

Column (2) is used in counterfactuals, though Columns (2) and (3) imply similar per-period costs of $27,000 before any applicable state subsidies. The estimated costs include annualized upfront direct project costs such as hardware and labor, indirect costs such as the time of employees in the charging network department to manage the project, as well as ongoing maintenance costs. Government subsidies typically only cover direct project costs.

As a sanity check on the model, the discounted net present value of total charging station costs can be estimated by assuming a discount rate (such as from a firm's weighted average cost of capital) and using a net present value of vehicle profits in Inequality 4. A charging station improves the network growth rate in the next period and the local or long-distance network where the station is placed in every future period. I calculate that Level 3 charging stations have average discounted net present costs ranging from $253,000 (with a 10% discount rate) to $504,000 (with a 5% discount rate). Given an average of 1.7 charging posts per station, these estimates imply total direct, indirect, and maintenance costs of $152,000 to $302,000 per charging post. Best available industry estimates from engineering calculations and grant applications[25] for *direct* costs range from $50,000 to more than $200,000 per charging post. My cost estimates are in line with industry estimates and suggest a discount rate on the higher end. I use per-period costs in counterfactual simulations and do not need to assume a discount rate.

6 Compatible Charging Standards

This section studies the impact of a counterfactual scenario with compatibility across different charging standards. I present the results in two steps. Section 6.1 presents the demand response from compatibility. Charging stations in the status quo from 2011 to 2015 are made compatible with all car brands. The number and location of charging stations are held fixed. In Section 6.2, firms optimize the number and location of stations in each period, taking into account consumer EV purchases and competitor charging station investments.[26]

Throughout the counterfactual analysis, other vehicle characteristics such as price, Level 3 charging capability, and electric range are held fixed to their values in the status quo; prices

[25] See, for example, TechCrunch in 2013, Rocky Mountain Institute in 2014, and Texas Commission on Environmental Quality in 2021 (persistent URLs embedded for each source).

[26] A compatibility policy that begins after stations and EVs of different standards have been introduced to the market can be evaluated by combining the approaches of Sections 6.1 and 6.2. All previously built stations keep their original locations and can be made compatible with all car brands via retrofits or Level 3 (fast-charging) adapters. This paper does not estimate the costs of retrofits or adapter development. Going forward, firms invest in new stations knowing that all other car brands can use all stations. See Simcoe and Farrell (2012) for a discussion of paths toward compatibility.

are held fixed to isolate the effect of charging compatibility. EVs can still be differentiated in charging network quality in the counterfactual, depending on whether they are capable of fast charging and whether their electric range allows them to drive between pairs of charging stations. Car manufacturers therefore can still choose charging station investments that are relatively more beneficial for sales of their own EVs.

Social welfare is the sum of consumer surplus and producer profits. As shown by Small and Rosen (1981) and Williams (1977), the change in consumer surplus from a comparison scenario to a counterfactual scenario, with market and time subscripts suppressed, is given by:

$$\Delta CS = \int_i \frac{1}{\alpha_i} \left[\left(\ln \sum_{j=1}^{J} \exp(\delta_j^1 + \mu_{ij}^1) \right) - \left(\ln \sum_{j=1}^{J} \exp(\delta_j^0 + \mu_{ij}^0) \right) \right] dF(\nu_i).$$

Following the notation of Section 4, $\alpha_i = \alpha + \sigma_p \nu_{ip}$ is the marginal utility of income, (δ_j^1, μ_{ij}^1) are the mean utility and individual deviations in the counterfactual scenario, and (δ_j^0, μ_{ij}^0) are the mean utility and individual deviations in the comparison scenario. Total consumer surplus is the integral over heterogeneous consumers i with attributes $\nu_i = (\nu_{ip}, \nu_{ik})$.

6.1 Compatible charging stations with stations fixed to status quo

Table 5 presents changes in EV sales from charging standard compatibility with charging station investments fixed to the status quo. The results sum over changes in quarterly sales from 2011 to 2015. Compatibility is applied to each charging quality measure separately in Columns (1) - (3). Column (4) presents the impact of compatibility over all charging quality measures on EV unit sales, and Column (5) shows percent changes.

Examining the impact of compatibility on one charging quality measure at a time highlights the relative advantages of each standard's EVs and charging network in the status quo. Figure 2 shows that the Chademo network started earliest and has the highest station count, followed by Tesla and Combo. Towards the end of 2015, Combo overtakes Tesla in station count. Figure 3 shows that Chademo and Combo stations tend to be located within or near cities, and Tesla's stations tend to trace routes between cities.

Table 5 Column (1) presents impacts on EV sales from compatibility in charging stations within cities. The high number of existing Chademo stations within cities leads Chademo EV sales (Nissan LEAF, Mitsubishi i-MiEV, and Kia Soul EV) to benefit least from local network compatibility. Tesla (Model S, Model X) gains the most among the standards. Level 3-capable EVs gain market share overall. Column (2) presents impacts from compatibility in inter-city stations, which determine the number of MSA destinations an EV can reach. Combo EVs (BMW i3, Chevrolet Spark EV, and Volkswagen e-Golf) gain the most from inter-city station compatibility. Combo and Chademo EVs have similar ranges, so Combo EVs benefit from being able to use the high number of existing Chademo stations. Chademo and Combo EVs receive limited benefits from access to the Tesla network due to their shorter range.[27] Chademo EV sales hardly change from inter-city compatibility and even fall slightly. The Tesla network gains new MSA destinations from its long-range vehicles being able to use Chademo and Combo stations. Column (3) shows that network growth rate helps new networks attract customers. In the counterfactual, Chademo maintains the same network growth rate in the periods before Tesla and Combo enter with their vehicles and stations. The growth of the combined network slows by the time Tesla and Combo EVs enter the market. With compatibility, Tesla and Combo can no longer differentiate with higher growth rates of their separate networks, and their EV sales decrease from this quality measure.

Columns (4) and (5) show the net impact of compatibility in all charging quality measures. The majority of gains in market share for Level 3-capable EVs come from stealing market share from the outside good, which is non-electric vehicles. Sales of Level 3-capable EVs, or EVs that can fast-charge, increase by 14,000 units, which is 9% of Level 3 EV sales and 3% of all EV sales. The inter-city portion of the network plays a relatively more important role in the overall impact of compatibility.[28]

6.2 Compatible charging stations with endogenous station investment

In each period, firms play a simultaneous-move game as described in Section 4. Firms choose where and how many new charging stations to build, which take one period to complete. Consumers maximize utility and choose between EVs and the outside option, taking into account the available charging network. To find an equilibrium of the firms' simultaneous-move game, I simulate firms playing iterated best response until no firm changes its strategy relative to the previous iteration. In each iteration, a firm conditions on other firms' investments from the previous iteration to solve its charging station investment problem.

[27] The average number of destinations more than doubles for Combo EVs from inter-city compatibility. Chademo and Combo EVs have lower electric range and cannot traverse the distance between Tesla stations placed between 100 to 150 miles apart. Tesla stations contribute 9% and 12% to the number of destinations reachable by Combo and Chademo EVs, respectively, when stations become compatible.

[28] The sales changes from Columns (1) - (3) do not add up exactly to Column (4) because the cross-partial derivatives of market share over product characteristics are nonzero.

I simulate a Social Planner to provide a benchmark for comparison to firms' charging networks from profit-maximization. The Planners' charging stations are compatible with all vehicle brands. The Planner has access to all three firms' charging station departments (cost functions) and can build charging stations at the lowest cost available. For any given number of charging stations, the Planner chooses locations to maximize consumer surplus. In each period, the Planner builds until the marginal cost of a charging station exceeds the marginal benefit to consumer surplus.

How far apart should the Planner's inter-city stations be placed? I simulate two versions of the Planner, differing only in the inter-city portion of the network. The constrained Planner builds inter-city routes with stations 50 miles apart so that they can be traversed by EVs of all available electric ranges, such as the lower-range Nissan LEAF or BMW i3 BEV. Serving the lowest EV ranges on inter-city routes is consistent with the spirit of compatibility and the current plan under the IIJA to subsidize charging stations every 50 miles along highways. The unconstrained Planner searches over routes with stations either 150 miles apart (which would only serve long-range EVs) or 50 miles apart. The unconstrained planner has the option of filling in 150-mile-apart routes in later periods. Although the unconstrained Planner may be less realistic as a policy option, as it uses public funds to build infrastructure that is only accessible to part of the market, the exercise may be helpful as a closer comparison to firms, who still get to differentiate their inter-city station spacing even with compatible stations.

Table 6 presents and compares the counterfactual outcomes from each of the four regimes: (1) Incompatible charging standards with firm charging investment, (2) Compatible charging standards with firm charging investment, (3) Compatible charging standards with *constrained* Planner charging investment, and (4) Compatible charging standards with *unconstrained* Planner charging investment. The first panel of Table 6 presents consumer surplus, producer vehicle profits, and social welfare. Over 2011 to 2015, private investment under compatibility (C) results in about \$400 million higher consumer surplus than under incompatibility (I). The constrained Planner (SP1) achieves about \$100 million lower consumer surplus than firms (C) with compatibility. This is because firms can differentiate the inter-city station spacing where it's profitable for them. The unconstrained Planner (SP2) which searches over both short- and long-range station spacing achieves \$300 million higher consumer surplus than firms under compatibility (C). The constrained Planner achieves lower consumer surplus because stations spaced 50 miles apart are less valuable on average. As the number of stations built depends on comparing marginal benefit to marginal cost, the constrained Planner also builds fewer stations. This exercise shows that mandated compatibility with investment by firms can perform better than even a Social Planner when the Planner is constrained to spacing them 50 miles apart.

Aggregate producer vehicle profits follow the same patterns as consumer surplus, though not all firms reap the same benefits from compatibility. BMW, with a late-arriving EV model and charging network, benefits in all counterfactual regimes. Nissan loses sales from the unconstrained Planner (SP2) relative to all other regimes because some routes are not accessible by Nissan's low-range EVs. Tesla, on the other hand, loses sales from the constrained Planner (SP1) relative to all other regimes because uniformly accessible inter-city routes erode some of Tesla's long-range advantage. Social Welfare is the sum of Consumer Surplus, Producer Vehicle, Profits, less Charging Station costs. Social Welfare is $650 million higher under compatibility (C) than incompatibility (I), and an additional $500 million higher with the unconstrained Planner.

The second panel of Table 6 presents the number of charging stations built under each policy regime. Compatibility changes firms' investment incentives in two ways. First, for any given existing network, a firm derives lower profits from investments when its competitors can also access it. Investment falls due to this channel. Second, for certain consumer demand substitution patterns, compatibility can turn charging station investments into strategic *complements* (from strategic substitutes with incompatible stations). Competitors' investments improve the quality of the network that a firm can access, which may increase the returns to any investments that the firm may consider[29]. For example, Tesla building stations between cities reduces the number of new stations that BMW or Nissan would need to build to connect the same cities and increases their returns per station. Investment can rise from this channel. Whether investments are strategic complements under compatibility and the net effect of the two forces depends on the empirical estimates of demand and cost parameters. Table 6 results show that firms invest *more* on net under compatibility compared to incompatibility. Consistent with intuition, most of the market share gained by firms in the compatible counterfactual (Panel 3 of Table 6) comes from the outside good. Charging compatibility increases sales of EVs by 4.3% compared to incompatibility.

Even when all stations are compatible, firms do not fully internalize the benefits of their investments for consumer welfare and other firms (such as from network effects). Firms thus build fewer stations and in places that are on average less socially useful than the unconstrained Planner (SP2).

[29] In a logit demand model and a linear product characteristic, firms' investments are strategic complements if the outside good share $s_0 \geq .5$. The outside good share in the EV market during the period studied is well above .5, but whether this result still holds with more flexible substitution patterns from random coefficients depends on empirical estimates from data.

Some firms can be worse off in the Planner's world. Panel 1 of Table 6 shows that Nissan loses profits with the Planner, which can be attributed to the Planner directing more stations toward the inter-city portion of the network and building half as many local stations as Nissan would.

Table 6 Panel 1 shows that firms earn higher profits from EV sales under compatibility. There are three potential explanations for why firms have not offered compatible standards without pressure from regulation. First, firms face a costly coordination challenge in agreeing upon how to achieve compatibility, such as through choosing the standard that all firms would offer or developing all combinations of bilateral adapters. Second, compatibility may not be a Nash equilibrium in the stage game of choosing standards and whether to offer interoperability. A firm can do better by taking access to competitors' networks and 'defecting' by not offering access in return, which they can implement through software restrictions or differential access pricing. Specifying a contract for compatibility and enforcing it may be costly. The social welfare benefits estimated from this paper could be considered an upper bound on society's willingness to pay for the costs of achieving compatibility. Lastly, incompatibility can decrease the threat of new entrants in EV manufacturing or charging networks. Entry using one of the three established standards under incompatibility is less attractive because the entrant can only use a subset of existing stations. Any entrant with a new standard would have to set up a costly charging network to be competitive against the incumbents with well-established networks.

This paper does not analyze the decisions of third-party charging firms, though by the early 2020s, third-party entry in Level 3 charging is still quite sparse. The strategic effects across car manufacturers studied in this paper do not apply to third-party charging firms. Compatibility would strictly increase the expected revenue of a potential third-party charging firm by expanding the set of potential customers to all EVs rather than only those on a specific standard. Therefore, consumer surplus from any third-party charging sector would unambiguously increase in the counterfactual.

7 Conclusion

This paper studies how firms compete in product markets by investing in complementary goods and how investment incentives change when those complements become compatible. The EV market itself is an important market to understand because it could become a larger presence in the automotive industry and carry large potential environmental benefits.

With fuel efficiency and environmental regulations becoming increasingly stringent, car manufacturers continue to add EVs to their lineup. The most recent sales figures for new vehicles from the 1st quarter of 2022 show that EVs reached 5% of market shares. Yet, different Level 3 charging standards persist in the U.S. market. The guidance document following the IIJA of 2021 takes one step toward charging compatibility by specifying that only SAE CCS (Combo) charging stations qualify for federal funds. Recently in 2023, major automakers including GM, Ford, Rivian, Volvo, and Mercedes-Benz have announced that they will join the Tesla charging standard in the coming years, first by producing vehicles on the Combo standard and offering an adapter to access Tesla's stations, and later by producing vehicles with only Tesla ports. The recent announcements by automakers do not divulge details about the transfers or contracts between the automakers nor whether charging will be priced differently for Tesla drivers and non-Tesla drivers.

The shift of the industry toward the Tesla standard in 2023 may be due to the confluence of manufacturers trying to meet government vehicle electrification targets and gasoline car bans announced for 2025 or 2030 as well as reliability issues with the networks of other standards that are holding back EV adoption. The reliability issues on non-Tesla networks could be caused by inherent technical problems with the Combo standard as well as incentive and agency issues arising from lack of vertical integration. The framework developed in this paper could be useful for studying how charging station investment will change with increasing compatibility in the industry and the specific planned changes in standards membership.

This paper presents and estimates a structural model of consumer vehicle demand with utility over the electric vehicle charging network. Consumers have tastes over the local usefulness of the charging network relative to their commuting patterns as well as over national traversability. The demand parameters are combined with a model of oligopolistic car manufacturers to recover vehicle markups and charging station costs. The simulated counterfactual results show that, under compatibility, firms would reduce investments in charging stations. Yet, the size of the electric vehicle market would still expand since consumers can access all stations. A compatibility policy would improve social welfare despite the cutback in car manufacturer charging station investment.

This paper motivates three lines of future work. First, the dynamic incentives in investment intended to influence the equilibrium number of standards remain unexplored. Second, this paper abstracts away from charging station pricing, as many networks offered free charging during the study period. The framework of this paper could be pushed to incorporate pricing and potential roaming fees that could arise as more firms announce their plans to join the Tesla standard. Third, and more generally, a deeper understanding of industries' ability and willingness to self-organize into a uniform standard or to make joint investments would inform antitrust and innovation policy.

Finally, this paper contributes to the understanding of the role of directed technological change in climate change policy. Although a market price on environmental damages from emissions and pollution may be part of the first-best solution, Acemoglu et al. (2016) develop an endogenous growth model to show that the optimal climate policy path includes both carbon taxes and research subsidies for clean technologies. Aghion et al. (2016) show that firms in the automobile industry respond to higher tax-inclusive fuel prices by innovating more in alternative fuel (electric, hybrid, and hydrogen) technologies. This paper suggests that in addition to market failures in the upstream innovation stage, other inefficiencies and market failures in downstream product markets can hinder technological change.

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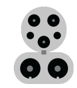
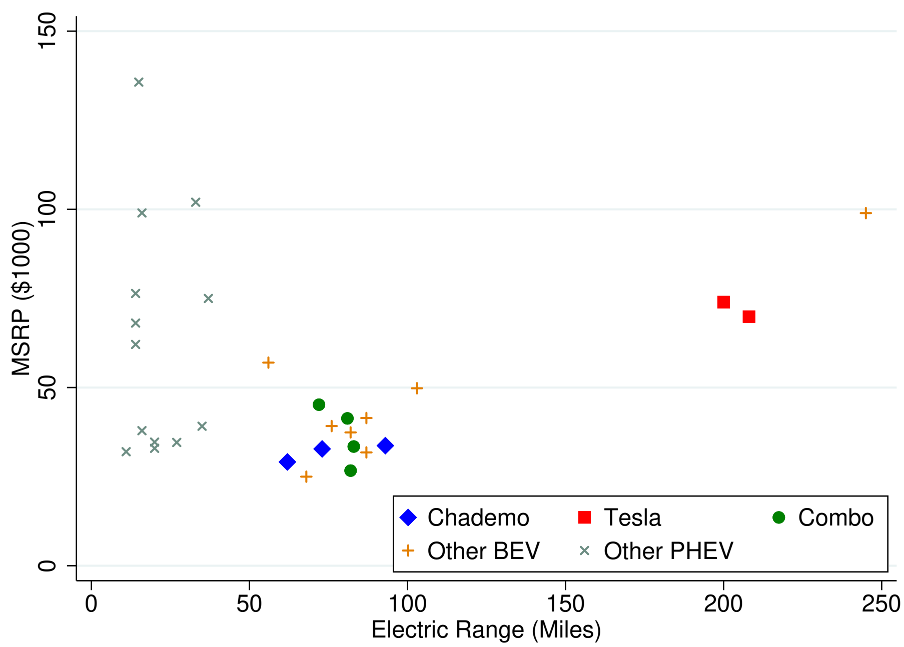
Figure 1: Charging Standards and EV Characteristics

(a) Level 3 (DC, Fast) Charging Standards

 Chademo	 Tesla	 SAE J1772 Combo
Nissan: LEAF Mitsubishi: i-MiEV Kia: Soul EV Toyota Peugeot Citroën	Tesla: Model S, X	BMW: i3 (PHEV and BEV) GM: Spark EV Volkswagen: e-Golf Ford Chrysler Daimler

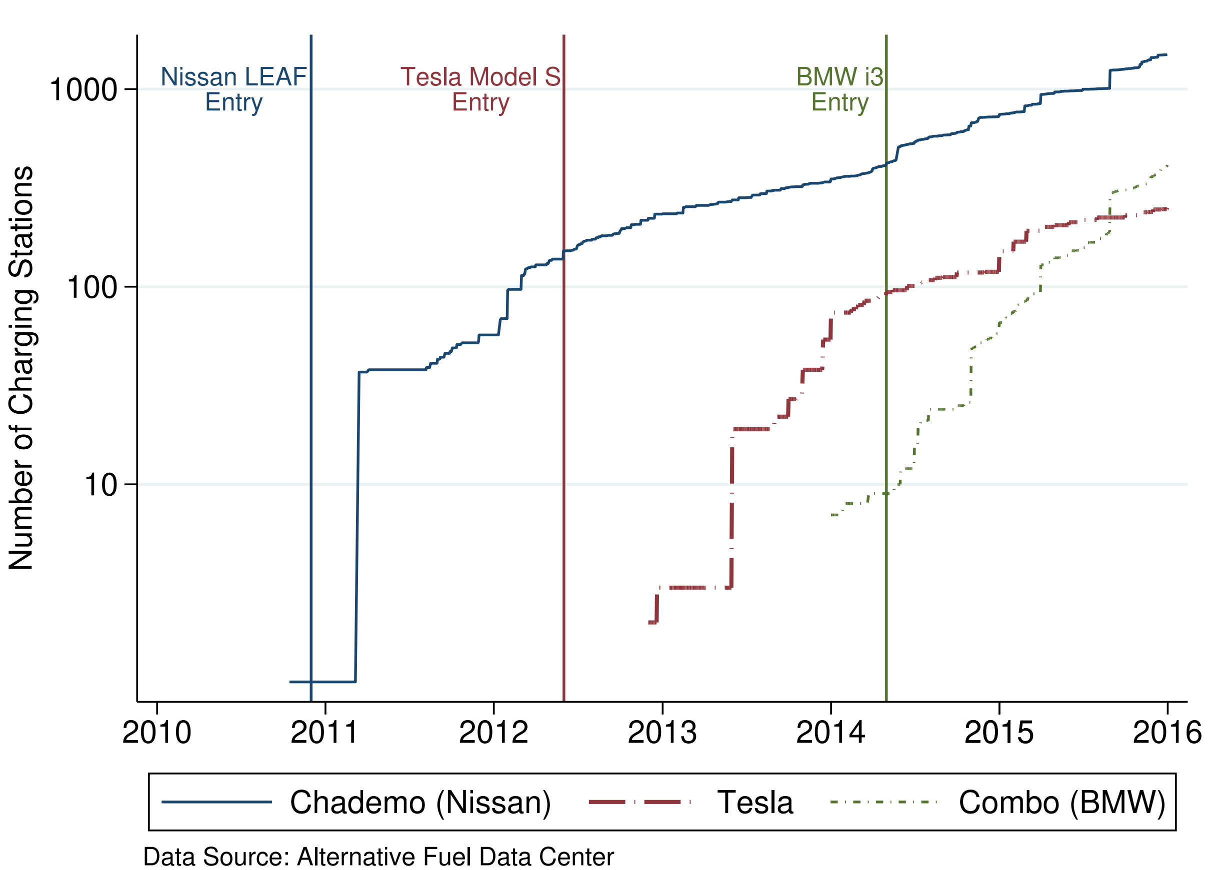
Depiction of plug shapes from Alternative Fuel Data Center

(b) MSRP and Electric Range of EV Models



Notes: Panel (a) depicts the connectors of each Level 3 (also called DC or fast) charging standard, along with the make and model of cars compatible with each standard as of the end of 2015. Only some EV models are capable of Level 3 charging. The listed automakers without vehicle models next to them had pledged to produce Level-3-capable EVs under that standard but had not yet done so by the end of 2015. Panel (b) plots the MSRP in thousands of dollars and electric range in miles of all EV models sold in the U.S. from 2011 to 2015. EVs compatible with each Level 3 standard are denoted by the symbols according to the legend. Other battery EVs (BEVs) and plug-in hybrid EVs (PHEVs) that cannot use Level 3 charging are denoted by "+" and "×" respectively.

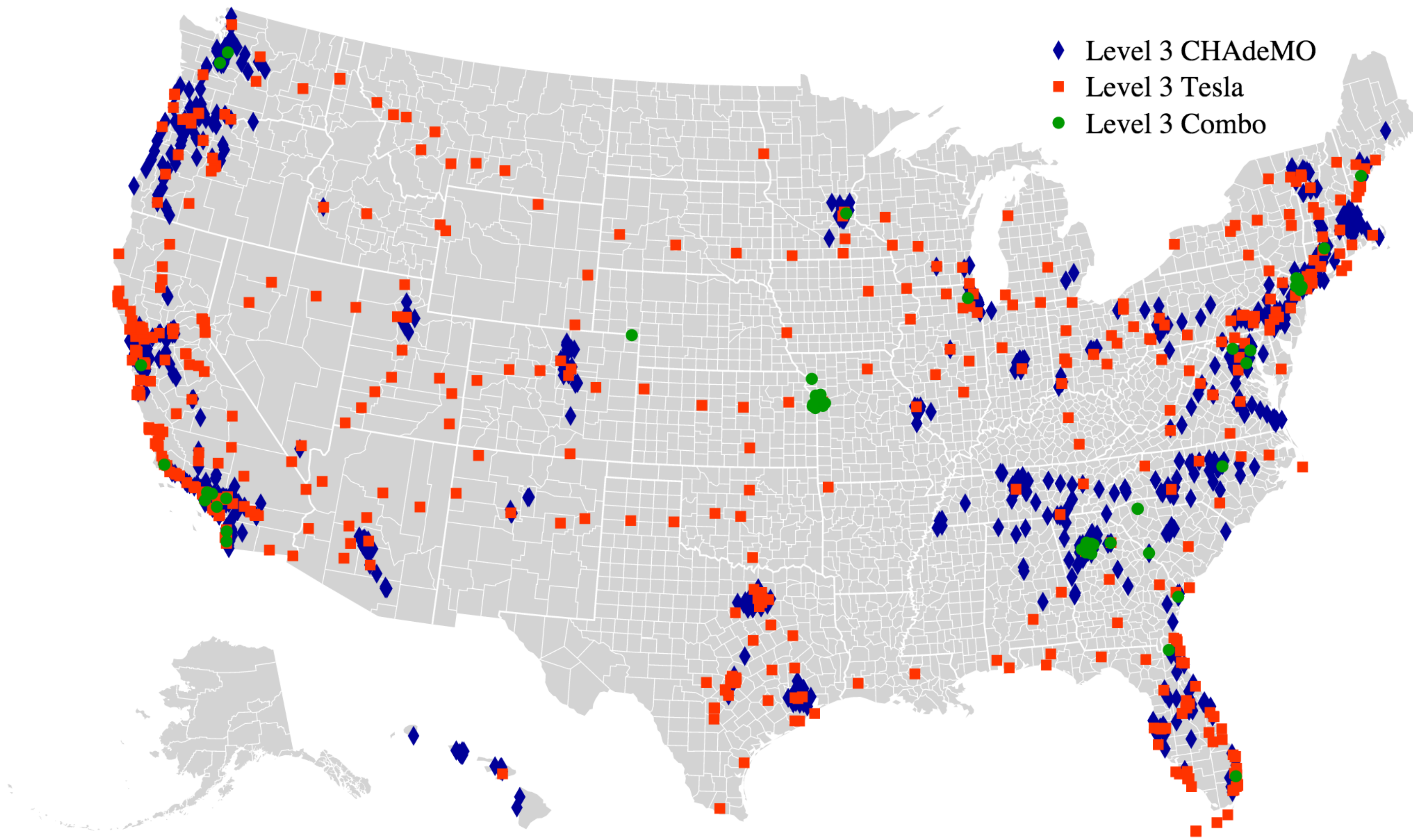
Figure 2: Charging Network Size over Time, by Standard



Notes: This figure shows the number of charging stations available over time for each charging standard. The y-axis is presented in log scale. Vertical bars mark when the first cars compatible with each standard became available in the U.S. market.

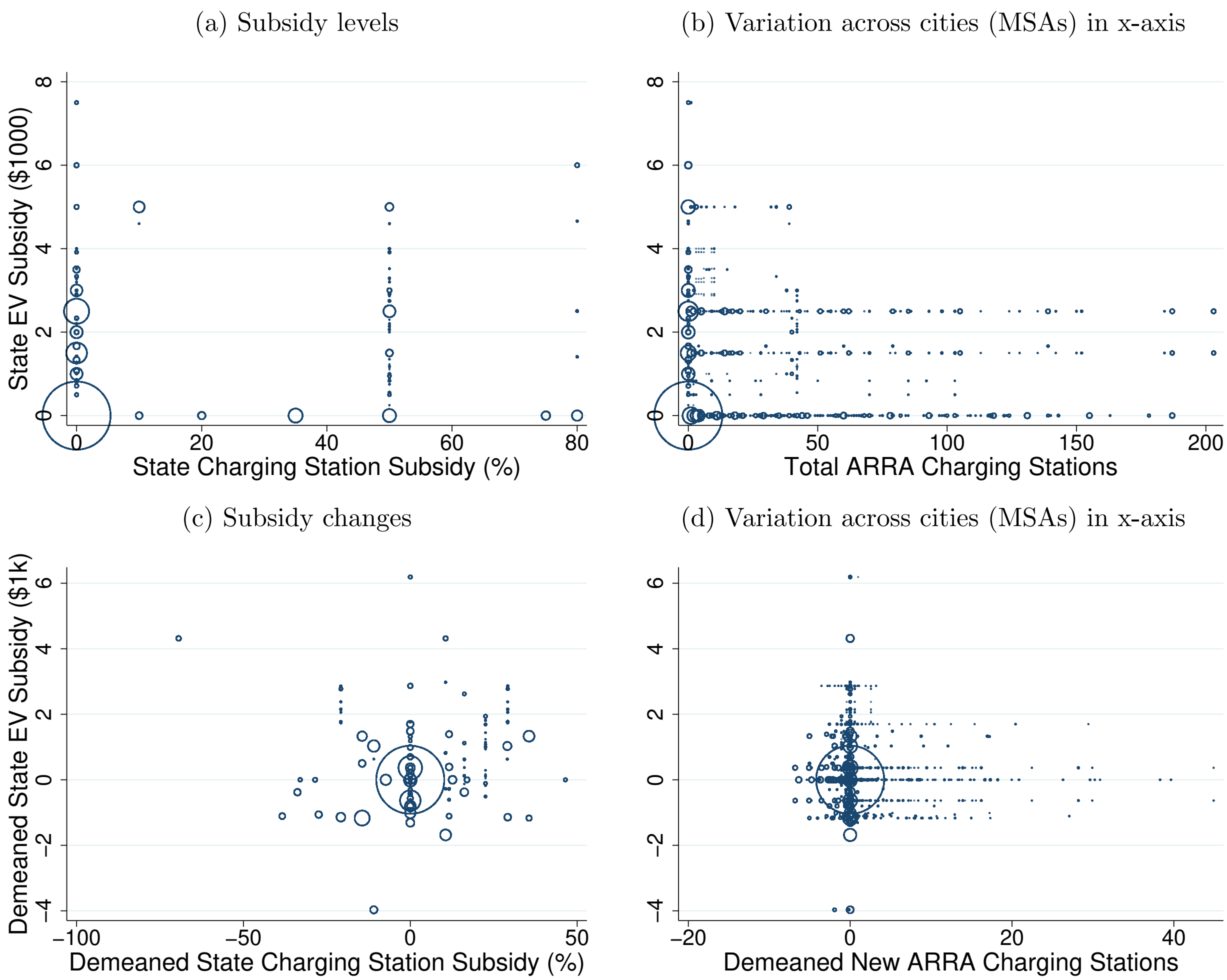
1. Nissan began deliveries of the Leaf in December 2010 and began building Chademo stations at the same time.
2. Tesla began deliveries of the Model S in June 2012 and announced the Tesla Supercharger program three months later, in September 2012.
3. BMW began deliveries of the i3 in May 2014 and announced a program to build stations under the Combo standard two months later, in July 2014. Before BMW i3's market entry, a total of 9 stations with the Combo standard were built at car dealerships.

Figure 3: Level 3 (DC, Fast) Charging Stations



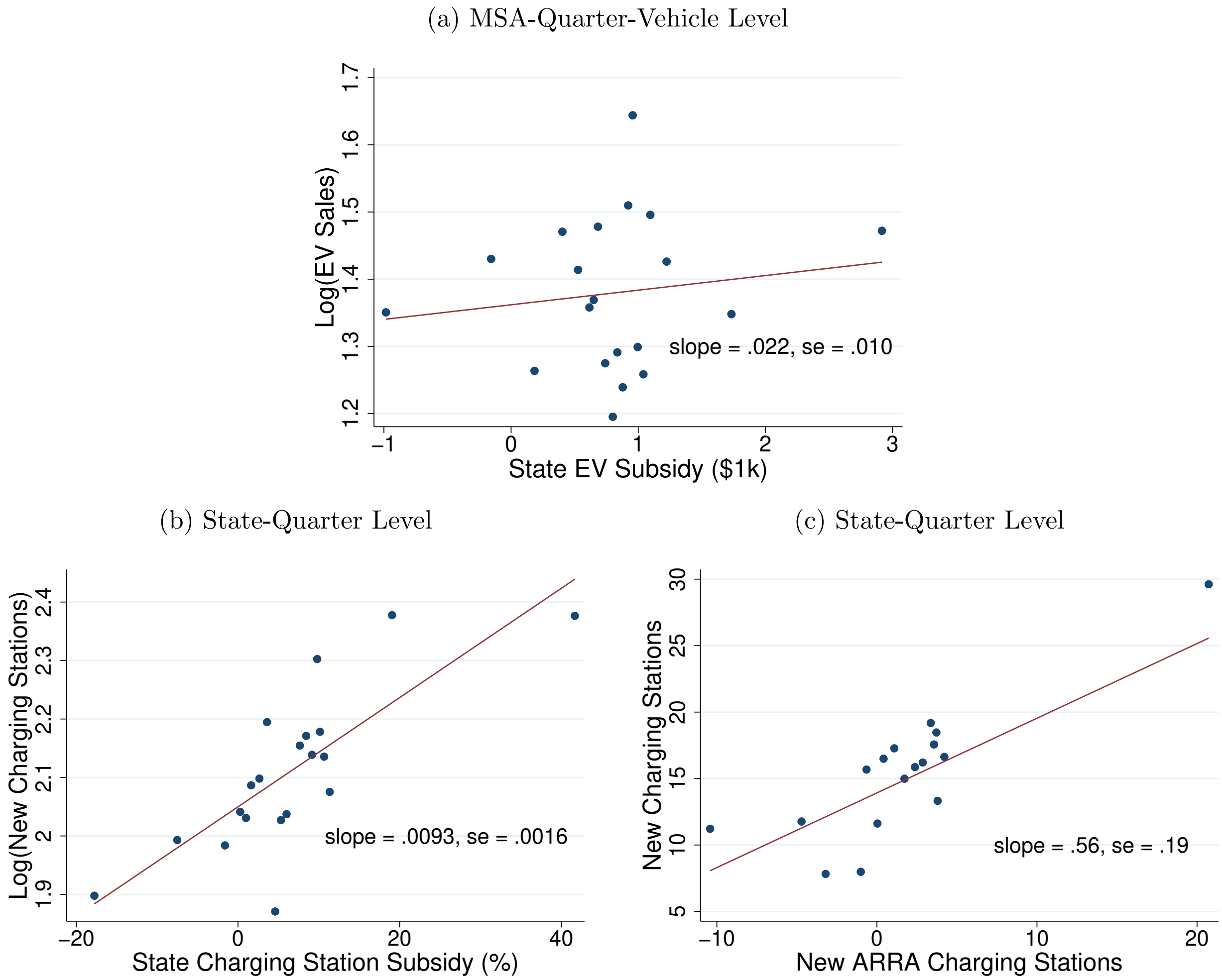
Notes: This figure shows where Level 3 charging stations are located for each standard as of September 2015, using data from the Alternative Fuels Data Center of the Department of Energy.

Figure 4: Independent Variation in EV and Charging Station Subsidies



Notes: This figure plots subsidies for EVs against subsidies for charging stations to show that incentives for vehicles and charging stations are allocated at different times and places. In all, circle sizes represent the number of observations (MSA-quarter-vehicle model) that take on that value. EV subsidies that vary by state, quarter, and vehicle model are scattered against the maximum charging station subsidies (over Levels 2 and 3) which vary by state and quarter in (a) and total stations funded by the ARRA, which vary by MSA and quarter, in (b). Demeaned EV subsidies are scattered against demeaned charging subsidies in (c) and demeaned counts of new stations funded by the ARRA in (d).

Figure 5: Relationship between Subsidies and EV Sales and New Charging Stations



Notes: This figure shows the relationship between subsidies for EV purchases and charging station investments and their targets. Panel (a) plots means of model-level log EV sales as a function of the state EV subsidy (controlling for market and quarter FE and observable vehicle characteristics such as electric range and BEV indicator) using a binned scatterplot. The line of best fit is generated from an OLS regression of model-level log EV sales on state EV subsidies with the same set of control variables. The reported standard error is clustered at the market-model level. Panel (b) and (c) examine the relationship between new charging stations and subsidies for them using binned scatterplots. Panel (b) plots the mean log number of new charging stations as a function of the maximum available charging station subsidy (lagged by one period because charging stations take one period to complete), controlling for state and quarter fixed effects. Panel (c) plots the mean number of new charging stations as a function of the number of newly arrived ARRA stations, controlling for state and quarter fixed effects. The line of best fit is shown in each. The reported standard errors are clustered at the state level.

Table 1: Evolution of Key Variables, 2011 to 2015

	2011	2012	2013	2014	2015
Markets with EVs For Sale	321	357	354	359	359
EV Models Available in the U.S.	3	6	15	22	27
EV Unit Sales	13,556	41,686	93,818	163,799	148,359
MSRP of EV Models (min)	32.78	29.12	25.00	23.00	23.00
MSRP of EV Models (mean)	56.96	45.71	49.61	47.27	48.46
MSRP of EV Models (max)	109.00	116.00	102.00	135.70	136.50
Electric Range (min)	35	11	11	11	11
Electric Range (mean)	117.67	48.33	64.80	65.00	63.33
Electric Range (max)	245	76	208	208	208

Notes: This table describes key variables of the U.S. electric vehicle market from 2011 to 2015, using vehicle registration data from IHS Automotive and vehicle characteristics data from MSN Auto. An electric vehicle (EV) is any vehicle that can be plugged in for recharging, including plug-in hybrids (PHEVs) and battery electric vehicles (BEVs). A market is defined as a metropolitan statistical area (MSA). The number of markets where EVs are available for sale increases over time because automakers take some time to roll out EV offerings across the U.S. The number of markets appears to decrease in 2013 because of idiosyncratic missing data from the data provider for 5 markets. MSRP is in thousands of dollars. Electric range is the number of miles a vehicle can travel starting with a full battery and, for a PHEV, using only the battery. Means are computed over EV models available each year.

Table 2: Unit Sales, Market Shares, and Empirical Bayes Posterior Market Shares

Variable	Mean	Std. Dev.	Min	10%	Median	90%	Max	% Zeros	N
EV Sales	11.2	58.0	0	0	1	16	2,727	36.4	41,224
2011	9.3	34.6	0	0	1	17	486	18.5	1,459
2012	10.7	49.5	0	0	2	17	1,126	23.5	3,887
2013	11.6	47.5	0	0	1	20	1,542	31.9	8,096
2014	13.6	72.4	0	0	1	20	2,727	33.4	12,041
2015	9.4	54.0	0	0	1	13	2,647	45.9	15,741
All Vehicle Sales	14,444.3	30,669.0	202	1,141	4,017	38,073	295,117	-	41,224
Observed EV Shares	0.00083	0.0019	0	0	0.00022	0.0023	0.133	36.4	41,224
Posterior Mean EV Shares	0.00080	0.0015	5.720e-12	0.000027	0.00033	0.0020	0.074	0	41,224

Notes: This table shows summary statistics of vehicle sales, observed market shares, and estimates of empirical Bayes posterior mean market shares. The data are from IHS Automotive from 2011 to 2015. Each observation is a MSA-vehicle model-quarter. The number of observations per year grows over time because more EV models become available and are offered in more markets. The top panel summarizes vehicle unit sales. The last row of the top panel shows total vehicle unit sales over all fuel types, which is also defined as the vehicle market size. For example, the maximum number of vehicles sold in any MSA-quarter is 295,117, in New York-Newark-Jersey City in the 2nd quarter of 2015. The bottom panel summarizes product-level shares of EVs, first observed shares followed by empirical Bayes posterior means. See Table 1 for the number of markets with EVs available and the number of EV models offered in the US, by year.

Table 3: Demand System Estimates

	(1) Logit OLS		(2) Logit IV		(3) Logit IV		(4) R.C. Logit	
	Param.	Std. Err.	Param.	Std. Err.	Param.	Std. Err.	Param.	Std. Err.
							Mean Valuation	
Price ($1000)	-0.05	(0.001)	-0.08	(0.004)	-0.09	(0.004)	-0.13	(0.021)
Log(Local Charging) $\times$ PHEV	0.02	(0.004)	0.03	(0.009)	0.10	(0.029)	0.23	(0.056)
Log(Local Charging) $\times$ BEV	0.001	(0.006)	0.003	(0.013)	0.07	(0.030)	0.21	(0.076)
MSA Destinations $\times$ PHEV	-0.12	(0.013)	-0.09	(0.022)	0.041	(0.028)	-1.24	(0.568)
MSA Destinations $\times$ BEV	0.003	(0.0002)	0.001	(0.0004)	0.004	(0.0004)	0.003	(0.022)
Charging Network Growth	0.12	(0.011)	0.23	(0.017)	0.25	(0.014)	0.33	(0.032)
BEV	-2.08	(0.025)	-2.08	(0.061)	-1.97	(0.055)	-2.51	(0.163)
Electric Range (10 miles)	0.14	(0.009)	0.12	(0.019)	0.12	(0.015)	0.12	(0.024)
Battery Capacity (10kWh)	-0.01	(0.032)	0.07	(0.068)	0.006	(0.055)	0.18	(0.095)
Power (100kWh)	0.74	(0.026)	1.54	(0.119)	1.78	(0.107)	1.58	(0.153)
All-Wheel Drive	1.19	(0.055)	2.34	(0.212)	2.29	(0.194)	1.70	(0.230)
Gasoline Price ($/gal)	0.07	(0.084)	-0.07	(0.099)	0.05	(0.087)	-0.10	(0.125)
Electricity Price (cents/kWh)	0.005	(0.011)	-0.004	(0.012)	-0.0001	(0.011)	0.001	(0.011)
MSA Income (per capita, $1000)	0.02	(0.009)	0.02	(0.011)	0.03	(0.011)	0.03	(0.012)
ρ, Autocorrelation of ξ	-	-	-	-	0.78	(0.009)	0.77	(0.009)
							Standard Deviation	
Price ($1000)							0.03	(0.006)
Log(Local Charging) $\times$ PHEV							0.04	(0.177)
Log(Local Charging) $\times$ BEV							0.00	(1.935)
MSA Destinations $\times$ PHEV							0.69	(0.220)
MSA Destinations $\times$ BEV							0.00	(0.270)
Observations	41,224		36,541		36,541		36,541	

Notes: One observation is a vehicle model available for sale in a market and quarter. All columns use the empirical Bayes posterior mean market shares. Logit in (1) is from OLS, logit in (2) is from 2SLS, logit in (3) uses the optimal weighting matrix from 2-step GMM and moments with innovations on ξ where relevant, and random-coefficient logit in (4) follows (3) while allowing for individual deviations in coefficients. All columns show robust standard errors clustered at the MSA-vehicle level. For (2), the weak instrument test statistic (Cragg-Donald Wald F-statistic) is 266.37. Charging network quality for each vehicle is captured by three measures: (i) number of local charging locations including Level 2 and Level 3, (ii) number of MSAs reachable from a given market using Level 3 locations and a vehicle's electric range, and (iii) growth rate of the Level 3 charging network.

Table 4: Charging Station Cost Parameter Estimates

	(1)	(2)	(3)
No. of New Stations	1.22	0.66	0.84
	(0.93)	(0.29)	(0.32)
Observations	60	60	60
Time Trend		X	
Time FE			X
Per-Period Cost ($1000)	38.56	26.83	27.06

Notes: One observation is a firm's charging station investment in a quarter. All columns use the marginal cost inferred from marginal profits and include a constant. Standard errors are robust. The bottom row "Per-Period Cost" is in thousands of dollars and is the average per-period cost that a firm would be willing to pay for a charging station.

Table 5: Demand Response to Compatibility (Charging Network Fixed to Status Quo)

	Change in EV Sales (US MSAs, 2011-2015)				
	Local	Inter-City	Growth Rate	All Charging Quality Measures	
	ΔQ	ΔQ	ΔQ	ΔQ	% Change
	(1)	(2)	(3)	(4)	(5)
Level 3-Capable	1,700	19,516	-6,055	14,370	9.0
Chademo Brands	297	-30	809	1,081	1.3
Combo Brands	582	13,702	-3,142	10,391	45.6
Tesla	820	5,845	-3,722	2,898	5.5
Non-Level 3-Capable	-68	-300	207	-161	-0.1
All EVs	1,632	19,217	-5,847	14,209	3.1

Notes: This table shows the consumer demand response to existing charging stations made compatible across all car brands, from 2011 to 2015. The charging network (number of charging stations and their locations) is held fixed to the status quo. Columns (1) - (3) show EV sales changes from each charging network quality measure while others are held fixed. Column (4) shows sales changes from all charging quality measures becoming compatible, and Column (5) shows percent changes. Figure 1(a) lists Level 3-Capable EV models for Chademo and Combo brands.

Table 6: Market Outcomes with Charging Standard Compatibility

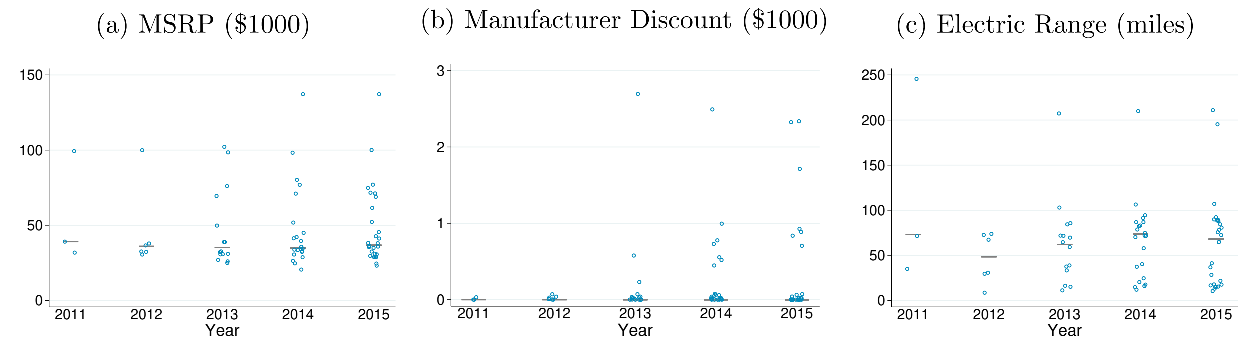
	Simulated Counterfactual Outcomes				Difference Across Regimes		
	Incompatible (I)	Compatible (C)	Constrained Social Planner (SP1)	Unconstrained Social Planner (SP2)	(C-I)	(SP1-C)	(SP2-C)
1. SOCIAL WELFARE $millions							
Consumer Surplus	5,070	5,468	5,352	5,795	398	-116	327
Producer Vehicle Profits	4,449	4,703	4,521	4,903	254	-181	200
Nissan	723	734	729	717	10	-5	-17
BMW	271	320	413	392	49	94	72
Tesla	606	813	533	963	207	-280	150
Social Welfare	9,427	10,076	9,776	10,590	649	-300	515
2. NUMBER OF CHARGING STATIONS							
Total Charging Stations	1,953	2,066	1,931	2,108	113	-135	42
built by Nissan	1,384	1,401	-	-	17	-	-
built by BMW	366	383	-	-	17	-	-
built by Tesla	203	282	-	-	79	-	-
3. EV UNITS SOLD							
All EVs	462,996	482,770	470,570	499,680	19,773	-12,199	16,910
Level 3-Capable	163,675	183,932	170,776	201,461	20,257	-13,157	17,529
Chademo Brands	85,769	86,987	86,486	85,053	1,218	-501	-1,934
Combo Brands	30,203	32,810	42,358	40,368	2,607	9,548	7,558
Tesla	47,704	64,135	41,931	76,040	16,431	-22,204	11,905
Non-Level 3-Capable	299,321	298,838	299,795	298,219	-484	957	-618

Notes: This table presents counterfactual market outcomes with: (1) Three incompatible standards and private charging investment, (2) Compatible standards and private investment, (3) Compatible standards and constrained Social Planner investment, and (4) Compatible standards and unconstrained Social Planner investment. Columns (4)-(6) compare outcomes across the specified pairs of regimes. Figure 1(a) lists Level 3-Capable EV models for Chademo and Combo brands.

Supplementary Appendix For Online Publication

A Additional Data Description and Estimates

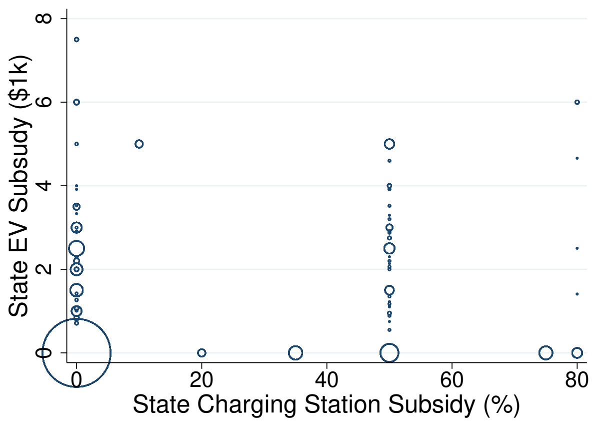
Figure A1: Distribution of EV Characteristics by Year



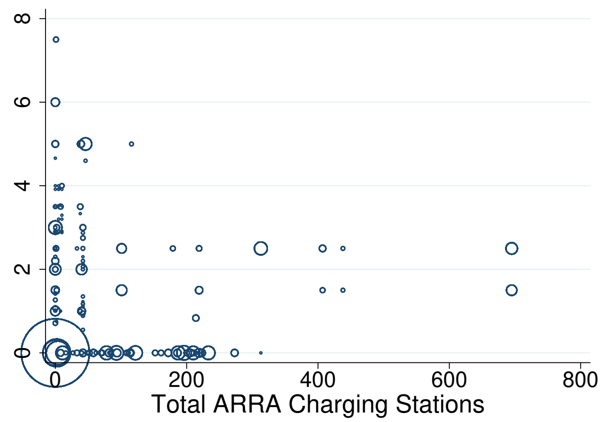
Notes: This figure shows the distribution of vehicle characteristics by year in jittered strip plots: (a) manufacturer suggested retail price (MSRP) in thousands of dollars, (b) manufacturer discounts in thousands of dollars, and (c) electric range (miles an EV can drive starting with a full battery, using only the battery). Each dot represents one EV model available for sale in a particular year. The column of points for each year shows the distribution of that vehicle characteristic along the y-axis. Points are shifted, or 'jittered,' horizontally within each year to better visualize close or overlapping data markers. The grey horizontal lines mark the median in each year. Table 1 reports, by year, the mean, minimum, and maximum for MSRP, electric range, and the number of EV models available.

Figure A2: Independent Variation in EV and Charging Station Subsidies, State-Year Aggregate

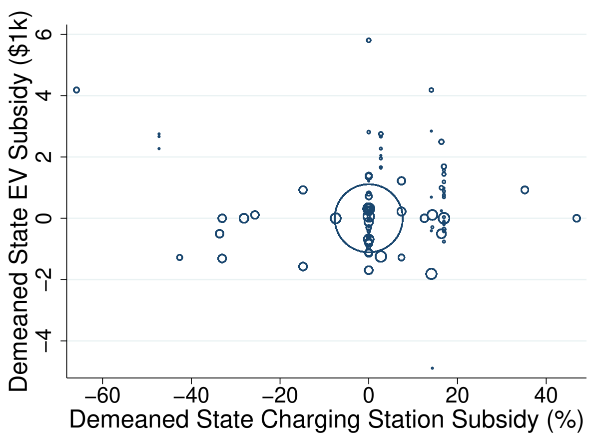
(a) Subsidy levels



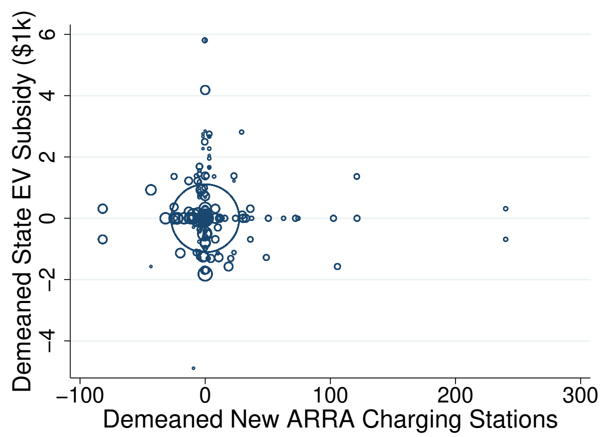
(b) Variation across states in x-axis



(c) Subsidy changes

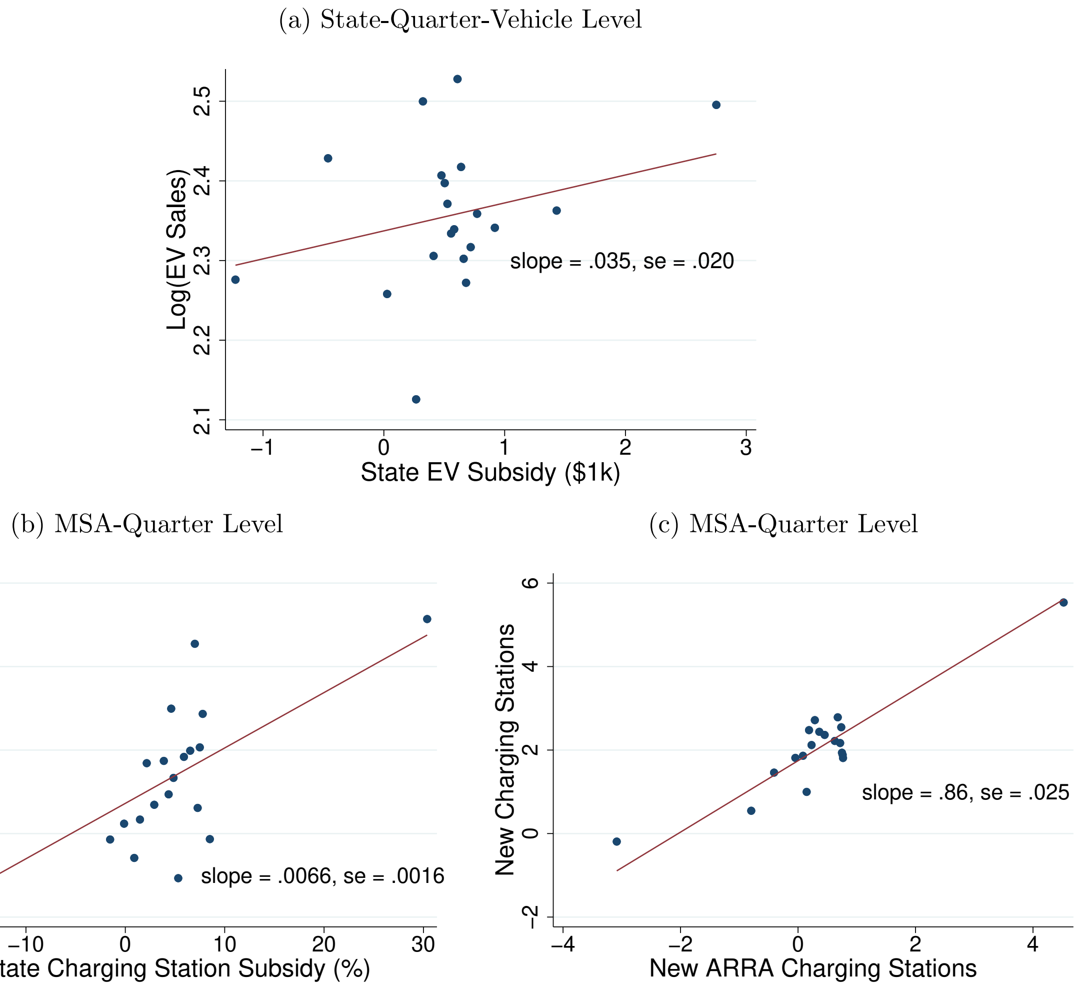


(d) Variation across states in x-axis



Notes: This figure plots EV and charging station subsidies to show that incentives for each are allocated at different times and places. In all, circle sizes represent the number of observations (state-year-vehicle model) that take on that value. State subsidies for EVs and charging stations that vary more frequently are aggregated to the yearly level. ARRA station counts are aggregated to the state-year level. EV subsidies are scattered against the maximum charging station subsidies (over Levels 2 and 3) in (a) and total stations funded by the ARRA in (b). Demeaned EV subsidies are scattered against demeaned charging subsidies in (c) and demeaned counts of new stations funded by the ARRA in (d).

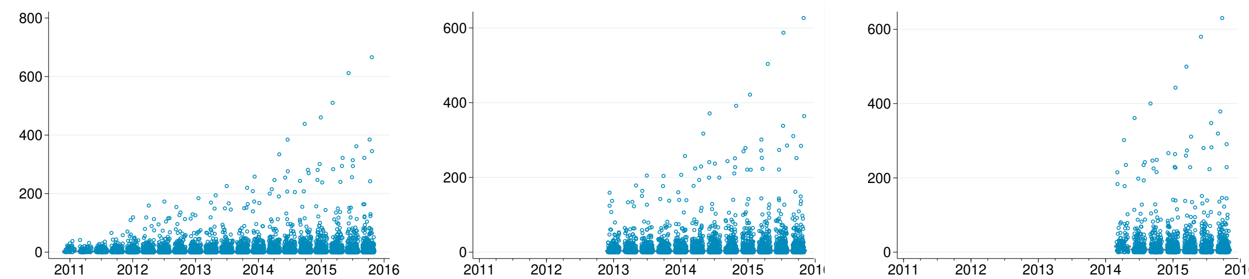
Figure A3: Relationship between Subsidies and EV Sales and New Charging Stations, Alternative Aggregation Specifications



Notes: This figure shows the relationship between subsidies for EV purchases and charging station investments and their targets. Panel (a) plots means of model-level log EV sales as a function of the state EV subsidy (controlling for market and quarter FE and observable vehicle characteristics such as electric range and BEV indicator) using a binned scatterplot. The line of best fit is generated from an OLS regression of model-level log EV sales on state EV subsidies with the same set of control variables. The reported standard error is clustered at the market-model level. Panel (b) and (c) examine the relationship between new charging stations and subsidies for them using binned scatterplots. The line of best fit is shown in each. The reported standard errors are clustered at the MSA level. Panel (b) plots the mean log number of new charging stations at the MSA-quarter level as a function of the maximum available charging station subsidy in the state, controlling for MSA and quarter fixed effects. Panel (c) plots the mean number of new charging stations as a function of the number of newly arrived ARRA stations, at the MSA-quarter level and controlling for MSA and quarter fixed effects.

Figure A4: Panel Variation in Local Charging Network Size

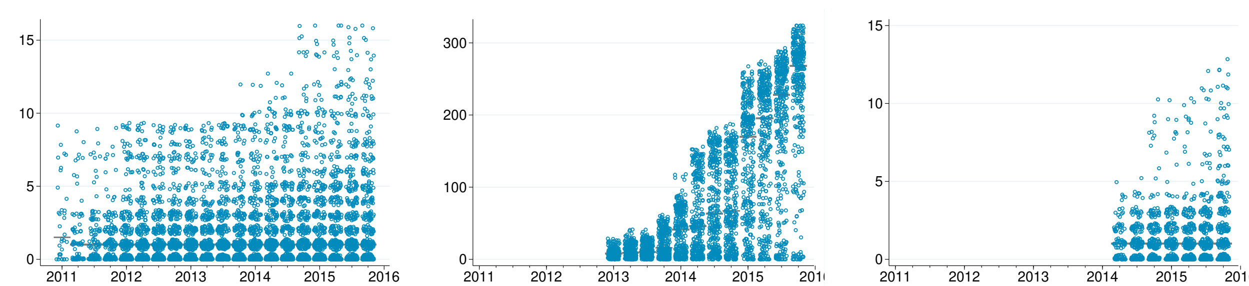
(a) Chademo (b) Tesla (c) Combo



Notes: This figure plots the number of Level 2 or 3 charging stations within each market (MSA) from 2011 to 2015, by quarter and charging standard. Each dot represents one MSA in a particular quarter, and the position of the dot along the vertical axis is the number of charging stations within that MSA.

Figure A5: Panel Variation in MSA Destinations

(a) Chademo (b) Tesla (c) Combo



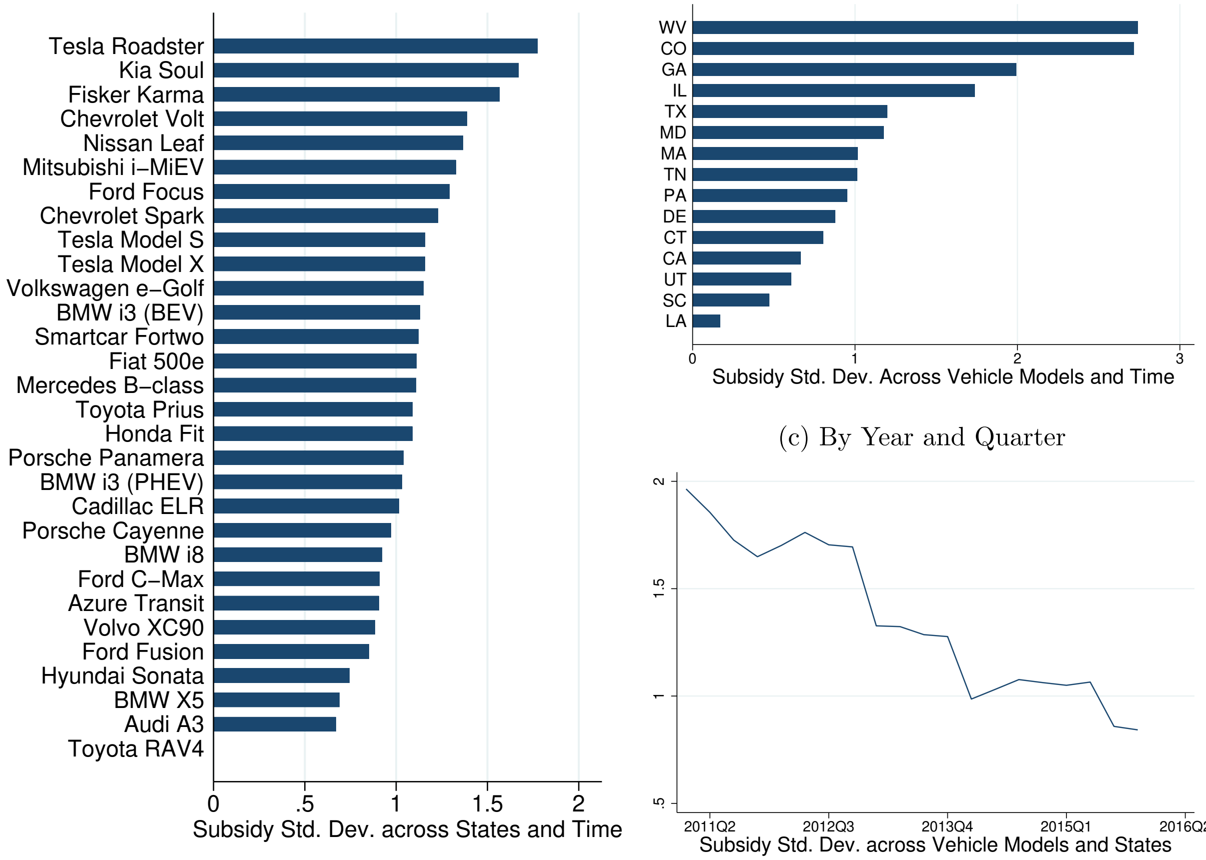
Notes: This figure plots the number of MSA destinations from each home market from 2011 to 2015, by quarter and charging standard. Each dot represents one MSA in a particular quarter, and the position of the dot along the vertical axis is the number of destinations possible from that MSA using the Level 3-capable EVs of each charging standard. The grey horizontal lines mark the median in each quarter. Conditional on being able to use Level 3 charging and the Level 3 standard, vehicles happen to have similar electric ranges. Therefore, for a given charging standard, quarter, and home MSA, there is no variation across vehicles in their number of destinations.

Figure A6: State Subsidies for EVs across State, Time, and Vehicle Model

(a) By Vehicle

(b) By State

(c) By Year and Quarter



Notes: This figure depicts variation in state-level subsidies for BEV and PHEVs from 2011 to 2015. The subsidies are manually collected from each state's legislative records. Subsidies vary across vehicle model, state, and time. The subfigures show standard deviations over each dimension separately. In (a), shortened brand and model names are displayed and refer to the electric version. For example, "BMW X5" represents the "BMW X5 xDrive40e," "Kia Soul" refers to the "Kia Soul EV," and "Toyota RAV4" refers to the "Toyota RAV4 EV." Sales of Toyota RAV4 EV are only observed in California, so there is no variation in subsidies for this vehicle model.

Table A1: Summary Statistics of EV and Charging Station Subsidies, 2011 to 2015

Variable	Mean	Std. dev.	Min	Max	Obs
Federal EV subsidy (\$1000)	6.27	1.83	2.5	7.5	41,224
State EV subsidies (\$1000)	0.75	1.31	0	7.5	41,224
ARRA station arrivals	0.36	2.33	0	50	41,224
State Level 2 charging station subsidies (%)	6.85	18.14	0	80	41,224
State Level 3 charging station subsidies (%)	4.89	15.96	0	80	41,224

Notes: This table presents summary statistics of government subsidies for EV purchases and charging station investments. The subsidy policies are described in Section 3.2. Observations are by MSA, vehicle model, and quarter.

Table A2: First-Stage Regressions and Independent Variation Among IVs

	(1) Log(EV Sales)	(2) Log(EV Sales)	(3) Log(New CS)	(4) Log(New CS)	(5) New CS	(6) New CS
State EV Subsidy ($1k)	0.022	0.019		-0.001		0.672
	(0.010)	(0.010)		(0.031)		(0.585)
State Charging Station Subsidy (%)		0.000	0.009	0.009		0.062
		(0.001)	(0.002)	(0.002)		(0.074)
New ARRA Charging Stations		-0.003		0.013	0.562	0.559
		(0.001)		(0.007)	(0.194)	(0.193)
Observations	26220	26220	1012	1012	1428	1428
MSA FE	X	X				
State FE			X	X	X	X
Time FE	X	X	X	X	X	X

Notes: This table presents the relationship between subsidies and their targets in Columns (1), (3), and (5). These relationships are also depicted in the binned scatter plots of Figure 5. "CS" is used for "Charging Station" in the column titles due to horizontal spacing constraints. Columns (2), (4), and (6) include the other subsidies to investigate whether the instruments offer independent variation. Standard errors are in parentheses and are clustered at the market-model level for (1) and (2), and state level for (2) - (6). The state charging station subsidies in (3) and (4) are lagged by one period because charging stations take one period to complete. Contemporaneous charging station subsidies are used in (5) and (6).

Table A3: Price Elasticities, Markups, and Marginal Costs

Variable	Mean	Std. Dev.	Min	10%	Median	90%	Max
Own-Price Elasticity	3.701	1.212	1.780	2.240	3.415	5.410	5.887
Markup	11.166	3.388	8.197	8.572	9.567	16.906	22.324
Vehicle Marginal Cost	45.104	24.117	20.423	21.987	37.505	83.334	113.842

Notes: This table reports price elasticities, charging station fixed costs, markups, and vehicle marginal costs calculated from the random-coefficients logit demand estimates from Table 3 combined with first-order conditions of the firms' profit function with respect to price. Each observation is a vehicle model.

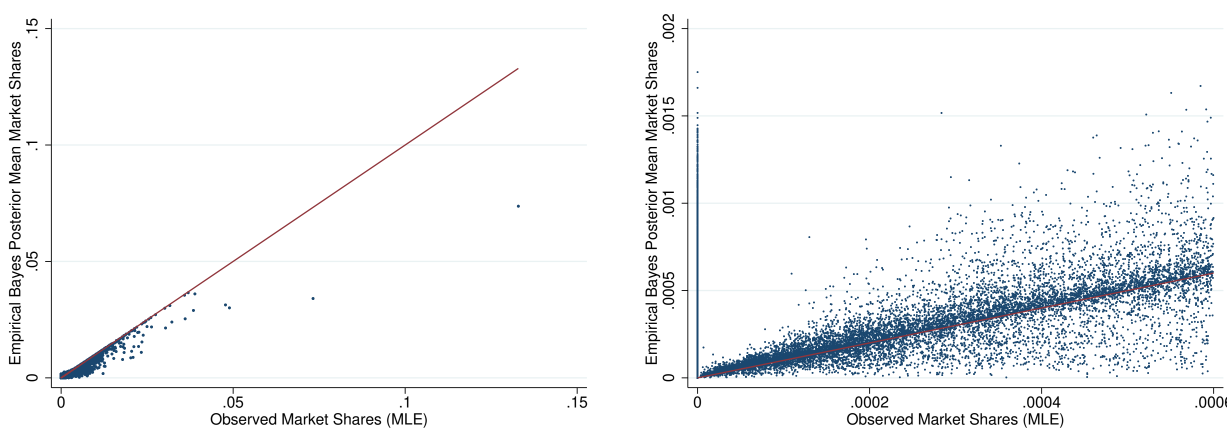
B Empirical Bayes Estimator for Market Shares

First, I describe alternative approaches to dealing with zero market shares. Next, I examine demand estimates from empirical Bayes priors of different sizes and the aggregation approach. Lastly, I discuss the methodological papers that treat zero market shares.

Priors of different sizes. The empirical Bayes posterior estimate is consistent with the demand model and, in the context of the needs of this paper's research question, has advantages over other approaches. The first common method is to aggregate to a larger market definition and average away the zeros. Aggregation would smooth over important spatial and time variation in charging station availability. The second solution is to add a very small constant to all the market shares. This is not ideal because the model may predict different purchase probabilities for two products that both have zero sales. Transforming zero shares into the same non-zero share is inconsistent with the demand model. In Figure A7(b), the spike at 0 on the x-axis (Observed Market Shares) shows that observed zero shares are mapped to different empirical Bayes posterior means. The third solution is to drop the observations with zero shares. This solution is not ideal because products that are known to be in the consumer choice set would be conflated with products that were not available to consumers at all. Consumers not purchasing a product in their choice set and consumers not having a particular product in their choice set at all have different implications for the underlying consumer preferences.

Figure A7: Empirical Bayes Posterior Mean vs. Observed Market Shares

(a) All Market Shares (b) Zooming In



Notes: This figure plots the empirical Bayes posterior means against the observed market shares. Each dot represents an MSA-vehicle model-quarter observation. Posterior mean estimates may be larger or smaller than the original observed market shares, represented in the scatter plots as being above or below the 45-degree line. Subfigure (a) shows all data points. Subfigure (b) zooms into the smallest market shares.

I first examine demand estimates from different empirical Bayes priors. Table A4 presents estimation results from a logit demand model using observed market shares and mean empirical Bayes market shares with priors of different sizes. Column (1) is produced from observed market shares. There are fewer observations because those with market shares of zero are dropped in estimation. Columns (2) through (6) use the mean empirical Bayes posterior, each with a different number of cities in the prior. The closest 10 cities in per capita income are in the prior for Column (2), the 30 closest cities in per capita income in the prior for Column (3), and so on. In Column (6), all other cities' market shares are used in the empirical Bayes prior. As a group, the empirical Bayes estimates differ from those produced using observed market shares in Column (1). The most noticeable differences are in the coefficients on price, charging network variables for BEVs, and the BEV indicator. Results from different priors in Columns (2) through (6) are similar, with some improvement in precision with more cities in the priors. These results show that the findings of the paper are robust to this choice of the number of cities in the empirical Bayes prior. The counterfactual and welfare results in the paper use 50 cities in the prior.

In Table A4, Column (1) differs from the later columns in two ways: (i) having fewer observations because zero shares are dropped, and (ii) shares being MLE rather than empirical Bayes posterior means. I investigate how these two differences contribute to the differences in coefficients between Table A4 Column (1) and the later columns. Table A5 presents the summary statistics of the different market share estimates. Panel A presents summary statistics of all data, and Panels B and C show statistics by nonzero and zero observed shares, respectively. In panels A and B, the empirical Bayes method produces market shares with similar means and lower variances compared to the observed shares. Empirical Bayes shares from different priors are similarly distributed. In panel C, the zero subsample, observed shares are 0, while empirical Bayes shares are pulled away from 0 based on the priors.

Table A6 presents demand estimates for the nonzero subsample. The empirical Bayes demand estimates (Columns 2 - 6) are closer to the observed share estimates in the nonzero subsample (Column 1), especially for the charging network coefficients and the BEV indicator. For example, in Table A6 the BEV coefficient estimated with observed shares is -1.084. The BEV coefficient estimated on the same nonzero subsample with empirical Bayes shares (50 cities in the prior, Column 4) is -1.246. Using the full empirical Bayes sample, including the observations that are observed zero shares, yields a BEV coefficient of -2.084 (Table A4 Column 4). The comparison between Tables A4 and A6 shows that including the observed zeros in some way (such as via the empirical Bayes estimator) could meaningfully change demand estimates. The demand estimates from the full sample (which is only possible by pulling the zero shares away from zero in some systematic way, such as with empirical Bayes posteriors) are preferred because the zeros contain information about consumers' preferences and should not be dropped.

Aggregation. Aggregation is a common approach to dealing with zero market shares. Aggregation can be over any of the dimensions available in the data. In the EV market setting of this paper,

Table A4: Logit IV Demand Estimates with Empirical Bayes Market Shares (All Data)

VARIABLES	(1) Observed	(2) EB 10	(3) EB 30	(4) EB 50	(5) EB 70	(6) EB All
Price ($1000)	-0.0689***	-0.0873***	-0.0801***	-0.0768***	-0.0756***	-0.0752***
	(0.00415)	(0.00651)	(0.00453)	(0.00416)	(0.00407)	(0.00397)
Log(Local Charging) × PHEV	0.0336***	0.0404**	0.0310***	0.0345***	0.0341***	0.0339***
	(0.00950)	(0.0171)	(0.00999)	(0.00875)	(0.00875)	(0.00864)
Log(Local Charging) × BEV	-0.0252	0.0157	0.0144	0.00437	0.00658	0.00519
	(0.0166)	(0.0258)	(0.0160)	(0.0129)	(0.0128)	(0.0126)
MSA destinations × PHEV	-0.0812***	-0.0655***	-0.0764***	-0.0825***	-0.0840***	-0.0787***
	(0.0202)	(0.0201)	(0.0188)	(0.0191)	(0.0192)	(0.0183)
MSA destinations × BEV	0.00209***	0.000164	0.000359	0.000940**	0.00106**	0.00110**
	(0.000428)	(0.000677)	(0.000481)	(0.000446)	(0.000438)	(0.000438)
Charging Network Growth	0.167***	0.264***	0.230***	0.229***	0.224***	0.221***
	(0.0186)	(0.0243)	(0.0182)	(0.0172)	(0.0169)	(0.0170)
BEV	-1.084***	-2.718***	-2.172***	-2.084***	-2.075***	-2.050***
	(0.0607)	(0.0963)	(0.0678)	(0.0606)	(0.0601)	(0.0584)
Electric Range (10 miles)	0.120***	0.174***	0.121***	0.132***	0.133***	0.137***
	(0.0187)	(0.0271)	(0.0190)	(0.0184)	(0.0183)	(0.0180)
Battery Capacity (10kWh)	-0.201***	0.0842	0.108	0.0368	0.0256	0.00416
	(0.0636)	(0.0976)	(0.0680)	(0.0655)	(0.0651)	(0.0640)
Power (100kWh)	1.247***	1.768***	1.616***	1.488***	1.461***	1.436***
	(0.110)	(0.181)	(0.128)	(0.117)	(0.114)	(0.111)
All-Wheel Drive	1.701***	3.021***	2.385***	2.276***	2.218***	2.237***
	(0.255)	(0.274)	(0.219)	(0.206)	(0.203)	(0.200)
Gasoline Price ($/gal)	-0.167*	-0.285*	-0.124	-0.0668	-0.0486	-0.0787
	(0.0939)	(0.165)	(0.107)	(0.0981)	(0.0969)	(0.0954)
Electricity Price (cents/kWh)	0.00266	4.88e-05	-0.0101	-0.00349	-0.00280	-0.00683
	(0.0129)	(0.0183)	(0.0138)	(0.0121)	(0.0116)	(0.0116)
MSA Income (per capita, $1000)	-0.00987	0.0569***	0.0239*	0.0226**	0.0175	0.0124
	(0.0110)	(0.0189)	(0.0128)	(0.0114)	(0.0110)	(0.0108)
Observations	21,782	36,541	36,541	36,541	36,541	36,541
R-squared	0.432	0.244	0.327	0.383	0.398	0.408
Mkt FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X

Notes: This table presents logit IV demand estimates for different market share construction approaches. Column (1) uses observed market shares and has fewer observations because zeros are dropped in estimation. Columns (2) through (6) use mean empirical Bayes (denoted "EB") posteriors as market shares, with different numbers of cities in the prior. Column (2) has 10 MSAs closest in per capita income in the prior, Column (3) has 30 MSAs, and so on, until Column (6) has all other cities in the prior. Standard errors in parentheses are clustered by MSA-vehicle model. *** p<0.01, ** p<0.05, * p<0.1

further aggregation across space is undesirable because the spatial variation in charging network quality is the main focus of the empirical analysis. I examine demand estimates from aggregation to the annual level. Market shares are defined as

$$\frac{\text{total model-level sales for each MSA over a year}}{\text{total vehicle sales for each MSA over a year}}.$$

There are 11,738 total MSA-vehicle model-year observations, of which 13.4% have zero market shares. In comparison, the MSA-vehicle-model-quarter specification has 41,224 observations, of which 36.3% have zero market shares.

Table A5: Summary statistics of Observed Shares and Empirical Bayes Posterior Shares

Variable	Mean	Std. Dev.	Min	Max	Obs
Panel A: All data					
Observed shares	.00083	.0019	0	.13	41,224
Empirical Bayes (10 MSAs in prior)	.00077	.0015	9.2e-15	.088	41,224
Empirical Bayes (30 MSAs in prior)	.0008	.0015	1.0e-13	.071	41,224
Empirical Bayes (50 MSAs in prior)	.0008	.0015	5.7e-12	.074	41,224
Empirical Bayes (70 MSAs in prior)	.00081	.0015	1.5e-13	.061	41,224
Empirical Bayes (All other MSAs in prior)	.00084	.0016	1.9e-07	.092	41,224
Panel B: Nonzero subsample					
Observed shares	.0013	.0022	3.5e-06	.13	26,220
Empirical Bayes (10 MSAs in prior)	.0011	.0018	6.3e-09	.088	26,220
Empirical Bayes (30 MSAs in prior)	.0012	.0018	2.0e-07	.071	26,220
Empirical Bayes (50 MSAs in prior)	.0012	.0018	2.3e-06	.074	26,220
Empirical Bayes (70 MSAs in prior)	.0012	.0018	2.4e-06	.061	26,220
Empirical Bayes (All other MSAs in prior)	.0012	.0019	3.3e-06	.092	26,220
Panel C: Zeros subsample					
Observed shares	0	0	0	0	15,004
Empirical Bayes (10 MSAs in prior)	.00019	.00026	9.2e-15	.0041	15,004
Empirical Bayes (30 MSAs in prior)	.00017	.00022	1.0e-13	.002	15,004
Empirical Bayes (50 MSAs in prior)	.00016	.00021	5.7e-12	.0018	15,004
Empirical Bayes (70 MSAs in prior)	.00016	.00021	1.5e-13	.0018	15,004
Empirical Bayes (All other MSAs in prior)	.00017	.00021	1.9e-07	.0016	15,004

Notes: This table presents summary statistics of observed market shares and empirical Bayes posterior shares. Panel A includes all observations (each observation is an MSA, quarter, and vehicle model). Panel B summarizes the market shares for the subsample of data where observed shares are greater than zero. Panel C summarizes the market shares for the subsample of data where observed shares are zero. In Panels A and B, the empirical Bayes shares closely match the observed shares in means and have slightly lower variance.

Estimates are robust to aggregating to the annual specification, though they become less precise. Table A7 presents logit demand estimates from the MSA-vehicle model-year specification. Zero market shares are dropped in estimation. Aggregated to the annual level, the quality of the local network is defined as the log of the average number of charging stations available in each MSA over the quarters of the year. The number of MSA destinations is averaged over the year. I define the network growth rate as the growth rate in the size of the network from the 4th quarter of a year relative to the 3rd quarter of the same year. All other characteristics are constant within the year or take the linear average for the annual value. Time FE are annual.

Column (1) of Table A7 presents OLS estimates. Compared to the MSA-vehicle model-quarter specification (Table 3 Column (1) in the paper), the coefficients on price, local charging network size, number of MSA destinations, and electric range are similar in magnitude and standard errors. The impact of network growth rate on annual market shares is about half (.0525) than its impact on quarterly market shares (.12). All remaining control variables have noticeably different magnitudes and standard errors. One possible explanation for the differences between the quarter and annual specifications is that the logit and BLP demand models gain some identification from variation

Table A6: Logit IV Demand Estimates with Empirical Bayes Market Shares (Nonzero Subsample)

VARIABLES	(1) Observed	(2) EB 10	(3) EB 30	(4) EB 50	(5) EB 70	(6) EB All
Price ($1000)	-0.0689***	-0.0827***	-0.0816***	-0.0801***	-0.0795***	-0.0782***
	(0.00415)	(0.00434)	(0.00421)	(0.00413)	(0.00413)	(0.00408)
Log(Local Charging) × PHEV	0.0336***	0.0395***	0.0355***	0.0321***	0.0315***	0.0323***
	(0.00950)	(0.00869)	(0.00829)	(0.00833)	(0.00832)	(0.00804)
Log(Local Charging) × BEV	-0.0252	-0.0124	-0.0218	-0.0259	-0.0257	-0.0323**
	(0.0166)	(0.0165)	(0.0160)	(0.0159)	(0.0159)	(0.0155)
MSA destinations × PHEV	-0.0812***	-0.0989***	-0.0947***	-0.0924***	-0.0922***	-0.0868***
	(0.0202)	(0.0223)	(0.0213)	(0.0212)	(0.0211)	(0.0199)
MSA destinations × BEV	0.00209***	0.00206***	0.00210***	0.00217***	0.00220***	0.00224***
	(0.000428)	(0.000419)	(0.000414)	(0.000410)	(0.000408)	(0.000410)
Charging Network Growth	0.167***	0.205***	0.205***	0.199***	0.196***	0.196***
	(0.0186)	(0.0180)	(0.0177)	(0.0175)	(0.0176)	(0.0176)
BEV	-1.084***	-1.355***	-1.278***	-1.246***	-1.238***	-1.208***
	(0.0607)	(0.0608)	(0.0594)	(0.0588)	(0.0585)	(0.0579)
Electric Range (10 miles)	0.120***	0.168***	0.158***	0.152***	0.149***	0.149***
	(0.0187)	(0.0191)	(0.0188)	(0.0184)	(0.0183)	(0.0182)
Battery Capacity (10kWh)	-0.201***	-0.315***	-0.287***	-0.272***	-0.264***	-0.255***
	(0.0636)	(0.0651)	(0.0639)	(0.0627)	(0.0623)	(0.0619)
Power (100kWh)	1.247***	1.500***	1.460***	1.424***	1.414***	1.375***
	(0.110)	(0.114)	(0.112)	(0.110)	(0.110)	(0.109)
All-Wheel Drive	1.701***	2.115***	2.126***	2.060***	2.043***	2.043***
	(0.255)	(0.283)	(0.278)	(0.272)	(0.271)	(0.267)
Gasoline Price ($/gal)	-0.167*	-0.201*	-0.184*	-0.149	-0.137	-0.117
	(0.0939)	(0.103)	(0.0992)	(0.0968)	(0.0962)	(0.0946)
Electricity Price (cents/kWh)	0.00266	-0.00339	-0.000339	-0.000382	-0.000396	-0.00236
	(0.0129)	(0.0129)	(0.0127)	(0.0127)	(0.0127)	(0.0128)
MSA Income (per capita, $1000)	-0.00987	-0.00718	-0.00466	-0.00387	-0.00625	-0.00841
	(0.0110)	(0.0117)	(0.0112)	(0.0110)	(0.0110)	(0.0108)
Observations	21,782	21,782	21,782	21,782	21,782	21,782
R-squared	0.432	0.375	0.394	0.405	0.408	0.427
Mkt FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X

Notes: This table presents logit IV demand estimates for different market share construction approaches, restricted to the subsample with observed shares greater than zero. Column (1) uses observed market shares and has fewer observations because zeros are dropped in estimation. Columns (2) through (6) use mean empirical Bayes (denoted "EB") posteriors as market shares, with different numbers of cities in the prior. Column (2) has 10 MSAs closest in per capita income in the prior, Column (3) has 30 MSAs, and so on, until Column (6) has all other cities in the prior. Standard errors in parentheses are clustered by MSA-vehicle model. *** p<0.01, ** p<0.05, * p<0.1

in choice sets. Aggregation to the annual level smooths over some changes in choice sets from exogenous product entry and exit.

Column (2) of Table A7 presents IV logit estimates. One set of instruments for the charging network variables is the lagged charging network quality from the previous period. At the MSA-vehicle model-year specification, the annual lag in the IVs causes a dramatic loss in the number of observations and leads to some seemingly nonsensical coefficients. For example, a larger local network would seem to *decrease* the desirability of both PHEVs and EVs. A negative coefficient on charging network quality suggests that charging stations may be built to boost EV demand in areas where demand would otherwise be lower, and instrumenting in the limited sample with available lags cannot overcome this selection effect. Assigning zeros to missing lags to preserve as many observations as possible does not change the results.

Column (3) of Table A7 presents IV logit estimates with *quarterly* lags as instruments. For example, the local charging variable is the log of the average network size over the quarters of a year. The lagged instrument is the log of the average network size from the 4th quarter of the previous year to the 3rd quarter of the year. In other words, the instrument is constructed from a window with a length of one year, rolled back by one quarter. The identifying assumption for this instrument to be valid is the same as in the MSA-vehicle model-quarter specification, namely that there's an innovation in the error term in the 4th quarter of the present year that is uncorrelated with the instrument, which is the charging network quality from last year's 4th quarter up to the 3rd quarter of the present year. The coefficients in Column (3) are economically similar to the IV logit estimates in the paper's main demand specification (Table 3 Column (2)). Some point estimates differ, though they have similar economic meaning. The specification of Column (3) has the benefit of aggregating sales from the year to smooth over some zero market shares while preserving the same identifying assumptions about the instruments and the evolution of unobservables.

The aggregation method and the empirical Bayes approach can produce similar estimates. The timescale of vehicle choice could plausibly be studied with quarterly as well as annual data. As Column (2) of Table A7 shows, the 5-year panel is a bit too short for the most straightforward analysis at the annual level. The hybrid version of Column (3), using market shares at the annual level and instruments with quarterly lags can produce estimates that have at least sensible signs. The specification of Column (3) also has a stronger first stage than Column (2), with Cragg-Donald Wald F statistics of 57.6 and 19.2 for Columns (3) and (2), respectively. The specification in the main text at the MSA-vehicle model-quarter level may be preferred because all variables and instruments take on the same level of disaggregation.

The empirical Bayes method can be a useful alternative to aggregation when important variation would be lost. The empirical Bayes method can be a helpful tool in other settings where aggregation may not be appropriate. For example, Levin et al. (2017) finds from a high-frequency dataset of city-level expenditures that estimating demand for gasoline at higher levels of spatial and temporal aggregation produces increasingly inelastic estimates. In the setting of this paper, some of the subsidy changes used for identifying variation occur within years at different times, suggesting that a time period shorter than a year may be preferred.

Other approaches to zero shares. Gandhi et al. (2023) discuss the small and zero market share problem in more detail and present an estimation framework to partially identify demand parameters. First, they pull market shares away from zero with a Bayesian posterior estimate founded upon Laplace's rule of succession. Next, they present a moment inequality approach to partially identifying demand parameters. The prior from Laplace's rule of succession assigns the same market share for each product, equal to $\frac{1}{J_{mt}}$, where J_{mt} is the number of products in

Table A7: Logit Demand Estimates with Aggregate (MSA-Vehicle Model-Year) Specification

VARIABLES	(1) OLS	(2) IV Annual Lag	(3) IV Quarter Lag
Price ($1000)	-0.0287***	-0.0689***	-0.0503***
	(0.00126)	(0.00449)	(0.00354)
log(Local Charging) × PHEV	0.0255***	-0.544***	0.0537*
	(0.00740)	(0.105)	(0.0323)
log(Local Charging) × BEV	0.000753	-0.594***	0.0225
	(0.0102)	(0.108)	(0.0356)
MSA Destinations × PHEV	-0.143***	-0.168***	-0.121***
	(0.0242)	(0.0326)	(0.0273)
MSA Destinations × BEV	0.00431***	0.00397***	0.00386***
	(0.000484)	(0.000669)	(0.000577)
Charging Network Growth	0.0525	1.370***	0.162***
	(0.0342)	(0.215)	(0.0357)
BEV	-1.456***	-1.502***	-1.457***
	(0.0573)	(0.101)	(0.0557)
Electric Range (10 miles)	0.123***	0.132***	0.146***
	(0.0168)	(0.0353)	(0.0156)
Battery Capacity (10kWh)	-0.218***	-0.207*	-0.302***
	(0.0591)	(0.110)	(0.0569)
Power (100kWh)	0.273***	1.195***	0.872***
	(0.0510)	(0.133)	(0.107)
All-Wheel Drive	0.405***	1.986***	0.946***
	(0.0864)	(0.253)	(0.132)
Gasoline Price ($/gal)	0.223***	-0.268***	0.140***
	(0.0339)	(0.0540)	(0.0412)
Electricity Price (cents/kWh)	-0.0340	0.0410	-0.0312
	(0.0222)	(0.0363)	(0.0225)
MSA Income (per capita, $1000)	0.00126	0.0475**	-0.00221
	(0.0121)	(0.0188)	(0.0121)
Observations	10,157	5,707	10,157
R-squared	0.442	0.361	0.413
Mkt FE	X	X	X
Time FE	X	X	X

Notes: This table presents logit demand estimates for data aggregated to the annual level. Each observation represents an MSA-vehicle model-year. Market shares are total model-level sales in each MSA and year divided by total vehicle sales in each MSA and year. The quality of the local network is defined as the log of the average number of charging stations available in each MSA over the quarters of the year. The network growth rate is the network growth rate from the 4th quarter of a year relative to the 3rd quarter of the same year. All other characteristics are constant or averaged over the year. Time FE are annual in the MSA-vehicle model-year specification. Column (1) presents OLS results. Column (2) presents IV logit results with instruments lagged by one year. Column (3) presents IV logit estimates with instruments lagged by one quarter. Standard errors in parentheses are clustered by MSA-vehicle model. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

the market. The assumption is that we know nothing about what the true purchase probabilities should be, besides that we have observed no purchases in this particular market. In my setting with panel data, the outcomes in other markets arguably contain information on purchase probabilities that can be exploited.

Lastly, two other sets of methods are available in the literature for dealing with zero market shares. First, Ackerberg and Rysman (2005) and Quan and Williams (2018) relax the i.i.d. assumption on the idiosyncratic taste term, the logit errors. In practice, this framework can be thought of as a random effects model which can allow for across-market variance in idiosyncratic tastes for a particular product and rationalizes zero market shares. However, it is not possible to recover the market-specific random effects, which are necessary to run counterfactual analyses. Second, Dubé et al. (2020) propose an estimator with a selection step using "consideration instruments" for whether a product will have positive sales.