

**DOCKETED**

<b>Docket Number:</b>	19-IEPR-04
<b>Project Title:</b>	Transportation
<b>TN #:</b>	228787-31
<b>Document Title:</b>	MIT Sloan School of Management - Compatibility and Investment in the U.S. Electric Vehicle Market - January 27, 2019
<b>Description:</b>	N/A
<b>Filer:</b>	Wendell Krell
<b>Organization:</b>	California Energy Commission
<b>Submitter Role:</b>	Commission Staff
<b>Submission Date:</b>	6/19/2019 9:22:42 AM
<b>Docketed Date:</b>	6/19/2019

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

Jing Li<sup>†</sup>

January 27, 2019

## Abstract

Competing standards often proliferate in 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 \$500 million; car manufacturers build 2.8% fewer charging locations and sell 20.8% more electric vehicles.

---

\*I thank my PhD advisors Christopher Knittel, Robin Lee, Ariel Pakes, James Stock, and Elie Tamer for their continual guidance and support. I thank Meghan Busse, 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, Yufei Zhao, Fanyin Zheng and participants in the Harvard Industrial Organization, Labor/PF, and Environmental workshop and lunches 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.

<sup>†</sup>MIT Sloan School of Management, lijing@mit.edu.

# 1 Introduction

When firms invest in incompatible complementary goods or technical standards, should the government intervene and mandate compatibility? This question generates fierce policy and antitrust debates in a wide range of industries, from digital markets to manufacturing because of the ambiguous welfare implications from mandating compatibility. 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, benefits to consumers may be offset by a decrease in firms' investments. Compatibility fundamentally changes the nature of competition among firms, turning 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, but they may invest too little under compatibility because private incentives do not internalize the positive spillovers. The theoretical 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 the large potential environmental benefits and innovation spillovers. Similar to other alternative fuel transportation technologies, including hydrogen and natural gas, electric vehicles require a refueling infrastructure for wider consumer acceptance. Accordingly, car manufacturers have invested heavily in building fast charging stations to refuel electric vehicles. To the chagrin of many consumers, however, car manufacturers have aligned themselves behind three mutually incompatible standards for fast charging. Incompatibility across three charging standards will become an increasingly focal policy issue, with the U.S. Department of Transportation's proposal to build 48 electric vehicle charging corridors on the national highways<sup>1</sup> (or similar programs in the future) and many utilities across the nation proposing to

---

<sup>1</sup>The White House Office of the Press Secretary. 2016. "Obama Administration Announces New Actions to Accelerate The Deployment of Electrical Vehicles and Charging Infrastructure." *Press Release*, November 3. <https://obamawhitehouse.archives.gov/the-press-office/2016/11/03/obama-administration-announces-new-actions-accelerate-deployment>

build charging stations<sup>2</sup>.

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 first five years of the U.S. electric vehicle market (2011-2015). Third, I use the model and parameter estimates to simulate market outcomes when all car manufacturers adhere to a single standard for recharging electric vehicles. I compare the status quo to the counterfactual market equilibrium and 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 rich geographic variation in consumer driving trips relative to charging station locations. The model also recognizes the importance of the connectivity of stations – how they are placed relative to each other and to driving origins and destinations – in addition to the sheer total number of stations that have been built.

I estimate the key parameters of my model using data on market-level vehicle sales and charging station characteristics, quantities, and locations. 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. 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. The exact timing of arrival of these Recovery Act charging stations, conditional on market and time fixed effects, are plausibly exogenous to unobserved product characteristics and contemporaneous local demand conditions.

I model car manufacturers as competing in static oligopoly. Combining demand

---

<sup>2</sup>Mulkern, Anne. 2016. “PG&E May Build Nation’s Largest Deployment of EV Charging Spots.” *E&E News*, August 26. <https://www.eenews.net/stories/1060042082>

parameter estimates and the first-order conditions of the profit function, I recover firms' markups for vehicles and costs for charging stations, which are 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. A firm's charging station build-out problem, conditional on the strategies of their competitors, is equivalent to a computational problem called "fractional knapsack" which has a simple and fast algorithmic solution. I find that some firms do have an incentive to cut back by 4.2% on station quantities under compatibility, though consumer surplus improves by about \$500 million and the number of electric vehicles sold increases by about 100,000, or 20.8%. The reduction in the number of charging locations under compatibility suggests that firms make excess investments when standards are incompatible. Indeed, the social planner would build 17.7% fewer locations compared to private investment choices under incompatibility. Surprisingly, the social planner builds fewer locations even compared to private investment choices with compatibility, which means firms do not invest too little relative to the social optimum. One way to explain this result is that even under compatible charging standards, vehicles remain differentiated in battery range. Therefore, the gains from compatibility are not symmetric, and firms can still benefit from spatial differentiation in their charging locations.

This paper contributes to three different literatures. 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 (2016)). However, firms' strategic responses to compatibility may moderate the gains in consumer welfare (Ishii (2007), Lee (2013), Knittel and Stango (2008, 2011)). After computing the counterfactual equilibrium charging network built by firms, I find that compatibility in charging standards improves consumer surplus by about \$500 million despite firms decreasing the number of charging locations 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 in order to compute welfare or solve for new product introductions (Wollmann (2018), Eizenberg (2014), Nosko (2014), Sweeting (2013), and Draganska et al. (2009)). In some settings, firms face a continuous choice space, such as in Crawford et al. (2015) and Fan (2013).

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 short-term environmental benefits of electric vehicles. They find high geographic variation in environmental benefits of electrifying transportation within the U.S, depending on the fuel mix of electricity production and population density. A second stream of this literature focuses on the design and impacts of subsidies for electric vehicles and other green technologies (Clinton and Steinberg (2016), 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. Using a two-sided market framework, Li et al. (2017) and Springel (2016) 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.<sup>3</sup> Recognizing the importance of charging station availability to the growth of the electric vehicle market, car manufacturers have become involved in building charging stations. 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 study 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, technical details about charging stations and standards, government policies, and the dataset. Section 3 specifies a model of consumer vehicle choice and car manufacturer investment in charging stations. Section 4 discusses identification, estimation, and results. Section 5 uses the model estimates to simulate market outcomes under a compatibility policy. Section 6 concludes.

---

<sup>3</sup>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

Institutional details and data availability motivate many aspects of my model. This section describes the growth of the U.S. electric vehicle market, charging standards and compatibility policy, the implications of government subsidies and Zero-Emissions Vehicle (ZEV) regulations for the electric vehicle market and this paper, and lastly, the data.

### 2.1 Growth of the U.S. electric vehicle market

Electric vehicles 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. Department of Commerce (2016)). Since Tesla Motors unveiled the first modern-day electric vehicle in 2006, a luxury sports car priced at more than \$100,000, automakers have been selling models that span a wide range of prices and features.<sup>4</sup> Electric vehicles 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. Unlike conventional hybrids, plug-in hybrids can be recharged by plugging into the electric grid. For example, the Toyota Prius first launched as a conventional hybrid in 2000, and in 2012 also became available as a plug-in hybrid. The unifying feature across both types of electric vehicles is that they are powered by rechargeable batteries and can be plugged in for recharging.

The electric vehicle market has expanded since its inception in late 2010 and is projected by industry analysts to grow much more in the coming decades. The 3 available models in 2011 collectively sold about 14,000 units in U.S. MSAs in 2011. By 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). With fuel efficiency and environmental regulations becoming increasingly stringent, car manufacturers have plans to add plug-in technology to most of their car portfolios. Car manufacturers have developed BEVs with higher battery ranges and lower prices, such as the Tesla Model 3 and Chevrolet Bolt, both launched in 2017. The number of charging locations for electric vehicles also grew ten-fold, with around 2,000 by the end of 2011 and around

---

<sup>4</sup>Technology for electric vehicles 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 electric vehicle market in recent years. See U.S. Department of Energy (2014) for a detailed account of the history of electric vehicles.

20,000 by the end of 2015.

Battery range and charging infrastructure are crucial for electric vehicles, analogous to tank size and availability of gasoline stations for gasoline cars. Battery range, the distance that an electric vehicle can travel starting with a fully charged battery, generally increases with the size of the battery. However, other factors, such as weight, aerodynamics, and anything else that impacts fuel efficiency also determine range. All electric vehicles can be recharged by plugging into an ordinary electrical outlet, so in contrast with cars of other fuel types, such as gasoline, hydrogen, or natural gas, dedicated refueling infrastructure may not seem obviously necessary. However, the ordinary outlet is very slow; it may be a reasonable option for overnight charging at home, but for travel distances that exceed the battery range, drivers need faster charging options away from home.

There are three speeds of charging options, increasing in power output and fixed costs of installation. Level 1 are the ordinary wall outlets used by most other consumer electronic devices. Level 2 charging stations can fully charge an electric vehicle in four to six hours, which make them suitable for destinations where drivers may park for a while. In residential homes, they can be attached to the outlet typically dedicated to laundry dryers and electric ovens. Some employers and owners of shopping malls, restaurants, and hotels have installed Level 2 charging stations as an amenity to their employees and customers. However, sessions lasting four to six hours are too long for many long-distance trips or for drivers who will not otherwise be parked for so long. The fastest charging stations are called Level 3, or direct-current (DC) fast chargers. These charging stations work in conjunction with a transformer to deliver high-power, DC electricity to vehicles. A 30-minute charge session can refuel a battery by 80%. Level 3 charging stations require the highest fixed costs out of all speeds because of the transformer and higher permitting, legal, and electrician labor costs.

## **2.2 Charging standards and compatibility policy**

Recognizing the importance of a fast refueling infrastructure for electric vehicle sales and due to the dearth of available Level 3 charging stations, automakers have entered the charging network market. Automakers have coalesced around three different Level 3 charging standards, each not compatible, or interoperable, with the others (Figure 1). In contrast, Level 1 and 2 charging standards are uniform across all vehicle brands



and have been built by employers, business owners, and government programs.<sup>5</sup> A charging standard has two parts: (i) a set of electronic communications between the vehicle and the charging station, and (ii) a physical connector.

Car manufacturers only began building the accompanying charging stations after the launch of fast-charging-capable BEVs, which suggests that firms invest in charging stations in order to boost vehicle sales (Figure 2). 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 Nissan’s BEV, the 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 Tesla’s BEV, the Model S. Meanwhile, other car manufacturers, working through the Society of Automotive Engineers (SAE), released the specifications of the SAE J1772 Combo<sup>6</sup> standard in October 2012. However, no cars were marketed under the Combo standard until the release of BMW i3 in May 2014. Two months later, BMW announced that it would build charging stations under the Combo standard.

Incompatibility in fast-charging protocols is a topic of vigorous policy debate and a potential source of social inefficiency. The European Union Parliament, with the objective of achieving a single charging protocol, ruled that all stations built after 2018 must at least be compatible with their chosen standard. In other words, multiple standards are allowed on each station via connectors or adapters (European Commission (2014)). Optimal policy regarding compatibility is an open empirical question.

### **2.3 Government subsidies and ZEV regulation**

Policymakers around the world and across levels of government have been supporting the growth of the electric vehicle market for a variety of reasons, including environmental benefits and innovation spillovers. Government subsidies and ZEV (zero-emissions vehicle) mandates have played a crucial role in the growth of the electric vehicle industry.

---

<sup>5</sup>The underlying reason for the lack of entry in building and operating charging stations to sell electricity for profit 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.

<sup>6</sup>Tesla vehicles may be sold with a J1772 adapter, but “J1772” without the “Combo” modifier is only the slower, Level 2 portion of the charge port. The “J1772 Combo” has as two DC pins under the regular J1772 port, hence the “Combo”. See Figure 1 for a depiction of each standard’s connectors.

I use panel variation in government subsidies for electric vehicle purchases as instruments for demand estimation. Electric vehicles face two main barriers to higher market shares: they are more expensive than comparable gasoline cars due to battery manufacturing costs, and they lack adequate refueling infrastructure. Federal income tax deductions in the U.S. for purchasing an electric vehicle range from \$2,500 to \$7,500, depending on the size of the battery. State income tax deductions on top of the federal incentives range from \$250 to \$7,500.

I construct two instruments from policy variation to identify the charging station elasticity of demand. The first instrument is a cost shifter. State governments subsidize charging stations, ranging from 10% to 50% of costs. The state subsidies for charging stations target businesses such as supermarkets, employers, rest-stops, and car manufacturers. The second instrument is the number of new stations in a city that are part of government-funded stimulus projects. In 2009, the American Recovery and Reinvestment Act (Recovery Act) allotted \$100 million to the Department of Energy to build charging stations. I discuss the identifying assumptions central to the validity of these instruments in Subsection 4.2.

Zero-emissions vehicle (ZEV) mandates designed by the California Air Resources Board require a growing percentage of automakers' overall sales to be zero-emissions.<sup>7</sup> Battery electric, plug-in hybrid electric, and hydrogen fuel cell vehicles satisfy ZEV regulations. The mandate is implemented and enforced through a tradable credit system. An automaker is assigned a credit requirement each year based on total sales volumes and that year's ZEV percent requirement. Each qualifying vehicle sold generates credits according to a formula that takes into account the battery range and other characteristics. For example, plug-in hybrids generate fewer credits than pure battery electric vehicles. Automakers are allowed to bank any excess credits toward future years as well as trade credits with other automakers. Although ZEV credit prices began to fluctuate in 2016, the maximum price of \$5,000 was binding in the data period of this paper, 2011-2015. I use \$5,000 as the value of each ZEV credit and include the value of ZEV credits in the firms' profit function.

---

<sup>7</sup>Under the Clean Air Act, states can choose whether to follow emissions regulations in California. California implements these mandates along with 9 other states. As of 2016, there are ten states with ZEV mandates: California, Connecticut, Maine, Maryland, Massachusetts, New Jersey, New York, Oregon, Rhode Island, and Vermont.

## 2.4 Data and descriptive statistics

My empirical analysis uses a dataset with five main elements. First, market-level information on consumer demand for cars comes from registrations of new vehicles, compiled by IHS Automotive (formerly R.L.Polk). These registrations are collected by each state’s department of motor vehicles and accurately reflect new car purchases. The dataset reports the number of registrations by car model, geographic area, and quarter. Each car model is defined as a brand, model name, model year, and fuel type. I use MSA delineations to define geographic markets. The panel includes 365 MSAs and 20 quarters, from 2011-2015. Second, the car quantities data are merged into model-level characteristics information from MSN Auto, the Environmental Protection Agency, and *Automotive News*, including manufacturer-suggested retail price (MSRP), manufacturer incentives, battery capacity, and fuel efficiency. The price that enters the firm profit function is the MSRP less manufacturer incentives. The price facing consumers is MSRP less manufacturer, federal, and state incentives. Third, I collected panel data on federal and state subsidies described in Section 2.3. Fourth, charging station investment data, including opening date, location, speed, and standard are published by the Department of Energy’s Alternative Fuels Data Center. Fifth, the National Household Travel Survey and the American Community Survey provide information on consumer heterogeneity in commuting flows and income.

## 3 Model

### 3.1 Model overview

My model consists of two main parts: consumer vehicle choice and car manufacturer profit maximization. The demand model is static in that consumers leave the market after their product choice and do not purchase again. It takes into account geographic variation in availability of charging stations and consumer heterogeneity in origin and destination of driving trips.

Car manufacturers play a series of static stage games. In each period, they first choose investments in charging stations to arrive in the next period. They next set prices conditional on the charging stations installed thus far and realized consumer demand shocks. Each period features the following sequence of events:

0. Station investments from the previous period arrive.

Vehicle models from exogenous R&D arrive.

1. Firms choose charging station investment.
2. Consumers realize demand shocks.
3. Firms set prices given demand shocks.
4. Consumers choose a vehicle to purchase.

### 3.2 Consumer demand

The main purpose of the consumer choice model is to predict the demand response to alternative quantities and locations of electric vehicle charging stations. I use a discrete-choice model following the framework of Berry et al. (1995) and Petrin (2002). Each period, consumers arrive at the market to purchase one of the inside goods, a plug-in car, or the outside good, a non-plug-in car. The demand model is static in that consumers choose myopically, without taking into account the future evolution of prices and other product characteristics, discussed in more detail later in this subsection. Therefore, the outside good does not include the option value of making the vehicle purchase decision in the future.

Consumer  $i$  chooses a vehicle  $r$  in market  $m$  and period  $t$ . Consumer utility from choosing one of the inside goods depends on consumer attributes and vehicle characteristics. It is given by:

$$U_{irmt} = \delta_{rmt} + \mu_{irmt} + \varepsilon_{irmt},$$

where  $\delta_{rmt}$  is the mean utility common to all consumers within a market and period,  $\mu_{irmt}$  are mean-zero individual deviations from mean utility, and  $\varepsilon_{irmt}$  are idiosyncratic tastes assumed to be i.i.d. logit.

Consumers derive mean utility,  $\delta_{rmt}$ , from purchase price,  $p_{rmt}$ , charging station access to be detailed later in this section, other characteristics,  $X_{rmt}$ , which includes a constant, and unobservable characteristics,  $\xi_{rmt}$ :

$$\delta_{rmt} = \underbrace{\alpha \log(p_{rmt})}_{\text{price}} + \underbrace{\gamma^S f_{rm}(G_t) + \gamma^L g_r(G_t, b_r)}_{\text{charging network quality}} + \underbrace{X_{rmt}\beta}_{\text{other chars.}} + \xi_{rmt}.$$

The individual deviations from mean utility,  $\mu_{irmt}$ , depend on consumer attributes

income,  $y_i$ , and average daily driving distance,  $d_i$ :

$$\begin{aligned} \mu_{irmt} = & y_i(\sigma_y^p \log(p_{rmt}) + \sigma_y^S f_{rm}(G_t) + \sigma_y^L g_r(G_t, b_r)) \\ & + d_i(\sigma_d^p \log(p_{rmt}) + \sigma_d^S f_{rm}(G_t) + \sigma_d^L g_r(G_t, b_r)). \end{aligned}$$

Demand parameters,  $\theta = (\theta_1, \theta_2)$ , can be categorized into the ‘linear’ parameters,  $\theta_1 = (\alpha, \gamma^S, \gamma^L, \beta)$ , and ‘nonlinear’ parameters,  $\theta_2 = (\sigma_y^p, \sigma_y^S, \sigma_y^L, \sigma_d^p, \sigma_d^S, \sigma_d^L)$ .

Consumers pay a purchase price  $p_{rmt}$ , which is equal to MSRP less manufacturer discounts (MD) and state and federal subsidies:

$$p_{rmt} = \text{MSRP}_{rt} - \text{MD}_{rt} - \text{State Subsidy}_{rmt} - \text{Federal Subsidy}_r. \quad (1)$$

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, and federal subsidies vary across vehicle models. Sallee (2011) finds that consumers capture the full federal and state incentives for the conventional hybrid car, the Toyota Prius, while Busse et al. (2006) find that manufacturer discounts are incompletely passed-through to consumers. Busse et al. (2006) hypothesize that subsidy pass-through increases with how much consumers know about the subsidies.

I will instrument for price in estimation, to be discussed in more detail in Subsection 4.2. If prices are measured with error, the price coefficient estimates will be valid if the instruments are uncorrelated with the measurement error. For example, if subsidies are passed through incompletely to consumers due to imperfect competition, then price coefficient estimates are valid if quarter and market fixed effects control for imperfect competition, or if the instruments are uncorelated with the time-market-varying component of imperfect competition.

The network size for each standard grows over time, and Nissan’s Chademo network vastly outnumbered the other two standards (Figure 2). However, a map of charging locations by standard shows the stark difference in how charging locations are distributed relative to urban centers and highway corridors (Figure 3). Tesla stations span the U.S. interstate highway system, while in contrast, Chademo and Combo stations cluster near urban areas. I model the value of charging networks as increasing in the number of charging locations as well as location match quality with consumers’ driving needs.

Consumers in the model take two types of trips: (i) local travel within the con-

sumer’s city of residence and (ii) long-distance travel between cities. In each period, the set of installed charging stations  $G_t$  is mapped to utils by the local travel function  $f_{rm}$  and inter-city travel function  $g_r$ .

This paper focuses on the importance of charging infrastructure away from consumers’ homes. Data from the Electric Vehicle Project show that about 22% of charge events occur away from home.<sup>8</sup> However, the percentage of charge events away from home is not necessarily proportional to its importance for electric vehicle adoption. I will infer the importance of charging stations by estimating the electric vehicle demand response to charging station arrivals.

Most drivers conduct all of their away-from-home charging at three or fewer charging locations. Drivers tend to charge at work, near commute destinations, and other public locations such as grocery stores or shopping malls (Idaho National Laboratory (2015))<sup>9</sup>. Therefore, the local travel function  $f_{rm}$  assigns a population-weighted count of the stations in set  $G_t$ , where the population weight is based on place of work rather than place of residence. The function  $f_{rm}$  further distinguishes between the number of Level 2 (slower) and Level 3 (fast) charging stations as well as the charging standard that vehicle model  $r$  is able to access. Consumers in the model have decreasing marginal returns from additional stations, captured by the log functional form:

$$f_{rm}(G_t) = \sum_{c \in \mathcal{C}_m} w_c (\log(N_{rct}^{l2}) + \log(N_{rct}^{l3})),$$

where  $N^{l2}$  and  $N^{l3}$  are the number of Level 2 and Level 3 charging stations, respectively. The population weights  $w_c$  for each county  $c$  in the set of counties  $\mathcal{C}_m$  in each market  $m$  (counties are wholly contained within MSAs, and geographic borders of counties align with MSA borders) are defined as:

$$w_c = \frac{\text{Population of market } m \text{ who drive to county } c \text{ for work}}{\text{Total population in market } m}.$$

This simple specification for the local travel function captures realistic and desirable spatial properties. Consider a city with residential counties surrounding a commercial core where everyone drives in for work. The commercial core would be the most

---

<sup>8</sup>The Electric Vehicle Project collected data on charging and driving behavior from about 5,800 Nissan Leaf and Chevrolet Volt drivers from 2012 to 2013.

<sup>9</sup>See Hardman et al. (2018) for a review of consumer interactions with electric vehicle charging infrastructure.

useful place for a charging location, because home charging is a superior substitute for charging locations in the residential area. Next, consider how public transit substitutes for driving. If few people drive to work in an MSA or to a particular county within an MSA because of ample public transit infrastructure, then the model would assign a low value to electric vehicle charging locations via a low numerator in the population weights  $w_c$ .<sup>10</sup>

In addition to enabling top-ups for commutes and errands, the set of stations  $G_t$  may also form a network that enables inter-city travel. The inter-city travel function  $g_r$  counts the number of city pairs that are connected by paths of Level 3 (fast) charging stations. Two cities are connected for vehicle  $r$  if a set of stations matching vehicle  $r$ 's charging standard traces a path between the cities and if the distance from one station to the next along the path is less than the battery range  $b_r$  of the vehicle:

$$g_r(G_t, b_r) = N_{rt}^{city\ pairs}.$$

To rule out unreasonable routes,  $g_r$  only counts a city pair as traversable if the path of Level 3 charging stations is at most 30% longer than the as-the-crow-flies distance. In estimation, I normalize  $g_r$  to be between 0 and 1. Tesla's charging locations outside MSAs are advertised as built for the purpose of enabling long-distance driving. The relationship between the number of connected cities and the cumulative number of charging locations is remarkably linear, as shown in Figure 4.<sup>11</sup>

I do not explicitly model the consumer costs of charging station access for three main reasons. First, Level 3 stations, the focus of this paper, are often free to use for the life of the car (Tesla) or for the first two to three years after purchase (Nissan and BMW). For these owners whose vehicles come bundled with free charging, the access price is zero. Second, Level 2 stations are primarily offered by third-party operators with a wide variety of nonlinear pricing schemes based on the number of minutes plugged in or the amount of electricity served. Some employers, retailers, and municipal governments subsidize access to particular stations on these third-party networks. Without any detailed data on charging station access pricing, a uniform scaling factor applied to

---

<sup>10</sup>My specification does not incorporate other features of the charging network, such as the dispersion of charging stations within counties. Constructing measurements of other features is feasible. However, demand parameters for these other features would be difficult to econometrically identify convincingly, and they would also make the firms' charging station investment decision computationally infeasible.

<sup>11</sup>The long-distance charging network build-out problem is slightly different from canonical graph theory problems, because two nodes (MSAs) only count as connected if the path between them is not "too much" longer than the shortest possible path.

all stations to account for an access charge would be absorbed by the constant in the utility function. Third, non-pecuniary costs of accessing charging stations - such as search, travel, and hassle costs - are implicitly built into the functions  $f_{rm}$  and  $g_r$ .

Firms' investments in charging stations during each period may be correlated with the unobserved product characteristic,  $\xi_{rmt}$ . For example, locally targeted advertising is unobserved and may be correlated with firms' investment choices. Moreover, firms may choose to build in markets with particularly low or high realizations of  $\xi_{rmt}$ . I address the endogeneity of price and investment in charging stations by instrumenting for both variables with a panel dataset of government subsidies, described in Section 2.3. Section 4.2 presents the formal identifying assumptions in more detail.

Modeling the vehicle purchase decision as static may be reasonable due to unique features of the electric vehicle market from 2011-2015. First, consider the scenario that consumers wait to purchase because they want the better products that will arrive in future periods, as in Gowrisankaran and Rysman (2012). Electric vehicle models on the market did not drastically change between 2011 and 2015. Due to limited advancements in battery chemistry and manufacturing processes, vehicles by the end of 2015 had similar range and prices as models released in 2011. Consumers who chose the outside option, a non-plug-in car, for the option value of a better electric vehicle in the future would have had to wait until 2017 for significantly longer battery range at lower prices, such as the Chevrolet Volt, 2018 model-year Nissan Leaf, and the Tesla Model 3. The most meaningful change in product characteristics, availability of charging stations, accrued to all electric vehicles that had been purchased. Therefore, the option value of waiting to buy a plug-in vehicle later may be limited.

A second justification of the static consumer demand model is that consumers cannot easily move homes or change workplaces in the short term. Therefore, purchasing a vehicle earlier due to anticipated future charging network improvements would imply an implausibly low weight on present-day driving needs. The static demand assumption can be interpreted as consumers placing predominant weight on the present, rather than assuming that consumers do not expect the charging network to continue to improve. A formal test of the importance of dynamic considerations will only be possible after the electric vehicle market has existed for a longer time.



### 3.3 Car manufacturer investment

My 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 that may be driven by firms' expectations of future periods beyond the time coverage of the dataset available. Therefore, my model of firms 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.

I also assume that vehicle characteristics other than price and charging stations evolve according to an exogenous product development process. This is a reasonable assumption given that the data period of 5 years from 2011 to 2015 is short relative to the product development cycle in the automotive industry overall and particularly in the electric vehicle segment. Blonigen et al. (2019) show that over vehicles of all fuel types, 70% of models are redesigned every 4 to 7 years, and an entirely new model takes even longer. The earliest electric vehicle models released in the 2011 model year came out with major updates only in late 2016, which is after the end of the data period.

The profit  $\pi_{jt}(G_t)$  of firm  $j$  in period  $t$  from its electric vehicle models  $r \in \mathcal{J}_{jt}$  is the sum over markups from cars sold minus the cost of charging station investment  $c(a_{jt})$ , given by

$$\left[ \sum_m \sum_{r \in \mathcal{J}_{jt}} \underbrace{(p_{rt} - mc_{rt} + ZEV_{rmt})}_{\text{per-car markup and ZEV credit}} \underbrace{s_{rmt}(G_t, p_{rmt}; X_{rmt}, \xi_{rmt}, \theta)}_{\text{mkt share}} \underbrace{N_{mt}}_{\text{mkt size}} \right] - c(a_{jt}), \quad (2)$$

where  $mc_{rt}$  denotes the marginal cost of producing car  $r$  in  $t$ .

In each period, firms simultaneously choose charging infrastructure investment  $a_{jt}$  that will arrive at the beginning of the next period, incurring cost  $c(a_{jt})$  and conditional on all the stations that have already been installed. Then, firms set prices  $p_{rt}$  to maximize profits. I model firms setting one price for the country for each model  $r$  and period  $t$ ,  $p_{rt}$ , which is the MSRP minus manufacturer discounts. The firm's price  $p_{rt}$  does not include government subsidies that are contained in the consumer-facing price  $p_{rmt}$ , defined in Equation 1. I do not observe and therefore do not take into account the region-specific discounts and dealer-specific nonlinear pricing contracts.

Firms choose the number of stations to allocate across 365 local networks and the inter-city network, so the infrastructure investment choice  $a_{jt}$  is a vector with 366 elements. The cost of  $a_{jt}$  is assumed to be linear in the total number of stations, given by,

$$c(a_{jt}) = \kappa|a_{jt}| + \omega_{jt}.$$

I model firms as maximizing profits from plug-in vehicles, ignoring externalities on other products in a firm’s portfolio, due to data availability and computational constraints. Two main arguments can justify this assumption. First, many car manufacturers have set up divisions dedicated to new electric models with unique physical styling. 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)). Second, institutional details suggest that the three firms explicitly modeled for charging station investment, BMW, Nissan, and Tesla, had zero or very little cannibalization in other segments over the time period of this study.<sup>12</sup> The remaining firms had not built charging stations by the end of 2015.

## 4 Estimation, Identification, and Results

In this section, I describe the estimation of the demand and cost parameters and how they are identified. I address the problem of zero market shares by shrinking the data toward an empirical Bayes prior formed over similar markets. This procedure pulls the market shares away from zero, which is important in order to apply 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 4.2 for how the demand parameters are identified and Subsection 4.3 for demand and supply estimation results.

---

<sup>12</sup>Tesla Motors sells only electric vehicles and invests heavily in its network of charging stations. BMW, the active firm in the SAE Combo standard, stated in a press release after selling the i3 for two years that more than 80% of worldwide i3 customers were new to the BMW Group (2015. <https://www.press.bmwgroup.com/global/article/attachment/T0242822EN/337735>). Nissan began designing the Leaf in 2006 to leapfrog the conventional hybrid car, a segment in which they were not competitive (Burgelman and Schifrin (2011)). Since then, Nissan has prioritized being the industry leader in zero-emissions and electric vehicles by championing the Chademo standard and investing in charging infrastructure worldwide (Nissan Motor Corporation (2012)).

## 4.1 Zero market shares

This paper studies the U.S. electric vehicle industry from its inception, when new car models initially sold zero quantities in some local markets. 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 sampled consumers’ multinomial draws. Each market is finite even when the consumer sample is the full population, and coupled with small purchase probabilities, the observed market shares include zeros. In my sample, 35.7% of market shares in any given model-market-quarter combination are 0, ranging from 15.5% (2011) to 45.5% (2015), as shown in Table 2.<sup>13</sup>

The true purchase probabilities underlying the observed market shares are unknown. Common practice in demand estimation is to use the observed market shares in place of the true purchase probabilities, which is implicitly using 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. (2017). 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 the 50 markets closest in income per capita, or about 13.7% of the 365 total number of markets.

I model the quantities purchased of each vehicle in each market,  $K_{rm}$ , as a draw from a binomial distribution with  $N_m$  trials and purchase probability  $s_{rm}^0$ . The time subscripts  $t$  have been suppressed throughout this subsection for simplicity. The purchase probabilities  $s_{rm}^0$  are different for each vehicle and market and are drawn from a Beta prior distribution with hyperparameters  $\lambda_{1rm}$  and  $\lambda_{2rm}$ . The total number of vehicles purchased is  $N_m$ . I choose this Beta-Binomial model of market shares for

---

<sup>13</sup>The number of zeros increases over time because the number of available plug-in models increases.

simplicity, though it can be generalized to a Dirichlet-Multinomial:

$$\begin{aligned} K_{rm} &\sim \text{Binomial}(N_m, s_{rm}^0), \\ s_{rm}^0 &\sim \text{Beta}(\lambda_{1rm}, \lambda_{2rm}). \end{aligned}$$

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

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

with posterior mean given by,

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

The observed shares, which are the MLE, are,

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

The strictly positive posterior mean,  $\hat{s}_{rm}$ , replaces the MLE, which contains zeros. In large samples, the empirical Bayes posterior would be very similar to the observed shares because the data would be informative enough to dominate the prior from other markets.

For each car  $r$  in market  $m$ , the Beta prior are formed using the 50 markets closest in per capita income,  $l \in \mathcal{B}_m$ , where  $l$  is a market from the set of similar markets  $\mathcal{B}_m$ . The parameters of the Beta prior,  $\lambda_{1rm}$  and  $\lambda_{2rm}$ , are estimated from maximizing the log of the likelihood over the outcomes in the markets that form the priors,

$$f(K_{rl}, l \in \mathcal{B}_m | \lambda_{1rm}, \lambda_{2rm}) = \prod_{l \in \mathcal{B}_m} \binom{K_{rl}}{N_l} \frac{\Gamma(\lambda_{1rm} + \lambda_{2rm}) \Gamma(\lambda_{1rm} + K_{rl}) \Gamma(N_l - K_{rl} + \lambda_{2rm})}{\Gamma(\lambda_{1rm}) \Gamma(\lambda_{2rm}) \Gamma(N_l + \lambda_{1rm} + \lambda_{2rm})}.$$

I estimate a pair of hyperparameters  $\hat{\lambda}_{1rm}$  and  $\hat{\lambda}_{2rm}$  for each vehicle, market, and period, and construct the posterior mean estimate of purchase probabilities,  $\hat{s}_{rm} = \frac{\hat{\lambda}_{1rm} + K_{rm}}{N_m + \hat{\lambda}_{1rm} + \hat{\lambda}_{2rm}}$ . As expected, the posterior estimates of market shares have lower variance, and all shares are strictly positive, as shown in the bottom panel of Table 2. Reassuringly, the means of the observed and empirical Bayes posterior market shares are quite similar, .00085 and .00082, respectively. Observed zero market shares have posterior mean estimates ranging from 5.5e-9 to .00162, as depicted in Figure 5(b).

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 estimator as true purchase probabilities. I assume that the same conditions hold when using the empirical Bayes estimator. Appendix A discusses the advantages of the empirical Bayes estimator over other common methods.

## 4.2 Identification

Firm investments in charging stations each period may be correlated with unobserved product characteristics. Therefore, additional instruments are required to identify the demand parameters compared to the usual instruments for price. I maintain the standard assumption that other product characteristics besides price and charging network are exogenous. I first discuss how I identify the price coefficient using variation from government subsidies. The identifying assumption is that the vector of instruments  $Z^{price}$  is orthogonal to unobserved characteristics  $\xi(\theta_2)$ ,

$$\mathbb{E}[Z^{price}\xi(\theta_2)] = 0. \quad (3)$$

I use three sets of instruments for price that are plausibly uncorrelated with unobservable characteristics  $\xi_{rmt}$ . The first two sets of instruments are federal and state subsidies. Since prices that consumers pay also include time-varying manufacturer discounts, the federal and state subsidies used as instruments are not the sole sources of variation in price. The third set of price instruments, the average characteristics of other products in the market (BLP instruments), are relevant because they affect the markups that firms can charge. The BLP instruments are uncorrelated with  $\xi_{rmt}$  given the assumption that the other product characteristics arrive as part of an exogenous development process.

Market and time fixed effects are included for all specifications. 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 (and enable 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.

Federal plug-in vehicle subsidies vary by car model and are determined by a piece-

wise linear function of the battery size. This instrument provides identification from the functional form, which I argue is uncorrelated with unobservables  $\xi_{rmt}$  after conditioning on battery size. It is reasonable to assume that policymakers set federal subsidies independently from  $\xi_{rmt}$ , because Congress approved and determined the structure of these plug-in vehicle subsidies as part of a stimulus package in 2009. I also assume that firms do not determine components of  $\xi_{rmt}$  based on the subsidy functional form.

State plug-in vehicle subsidies vary by state and vehicle model and change 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 across car models within states are uncorrelated with product unobservables  $\xi_{rmt}$ . Anecdotes of the state legislative process support the identifying assumption that the timing of subsidy changes are plausibly random. For example, some states enact laws that are effective immediately, others enact laws that are effective for the next tax (calendar) year beginning in January, while others enact laws that are effective for the next fiscal year beginning in July. The structure of state subsidies are also plausibly exogenous after controlling for characteristics that these subsidies condition on, such as battery size. Appendix B shows the variation in state subsidies for electric vehicles and charging stations over markets, time, vehicle models, and charging speeds.

Additional assumptions on the distribution of unobservable characteristics  $\xi_{rmt}$  and the instruments are necessary to identify the charging station coefficients. I assume that unobserved product characteristics  $\xi_{rmt}$  evolve according to a first-order autoregressive process,

$$\xi_{rm,t}(\theta_2) = \rho \xi_{rm,t-1}(\theta_2) + \nu_{rm,t}(\theta_2),$$

that  $\nu_{rm,t}$  are mean zero, independent across vehicle models  $r$ , markets  $m$ , and time periods  $t$ , and that

$$\mathbb{E}[Z^{station} \nu(\theta_2)] = 0 \tag{4}$$

for a vector of instruments  $Z^{station}$ .

I use three sets of instruments for charging stations that are plausibly uncorrelated with innovations in demand unobservables,  $\nu_{rmt}$ . First, similarly to the vehicle price subsidy instrument, state subsidies for charging stations are cost shifters that are uncorrelated with demand shocks conditional on market and time fixed effects.

The second set of charging station instruments are the number of new stations that are funded by the Recovery Act of 2009. As described in Section 2.3, recipient cities

were chosen before electric vehicles arrived to the U.S. market. Each city received the same number of stations predetermined by program funding availability, independent of the realized evolution of the electric vehicle market in each city. Regulators may have chosen recipient cities where they expected the highest growth rates or marginal impacts in 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  $\nu_{rmt}$ . In the data, Recovery Act stations arrive between the 2nd quarter of 2011 and the 2nd quarter of 2014. Similarly, car manufacturers may invest differently in response to the Recovery Act charging stations. If so, the assumption that stations take at least one period to be built means that the arrival of car manufacturers' stations are uncorrelated with contemporaneous  $\nu_{rmt}$ .

The third set of charging station instruments are the one-period lags of the charging station quality variables. The stations arriving in the beginning of period  $t$  were chosen by car manufacturers based on  $\xi_{rm,t-1}$ , before  $\nu_{rm,t}$  were realized. Therefore, new stations arriving in period  $t$  are uncorrelated with  $\nu_{rm,t}$ .<sup>14</sup>

### 4.3 Estimation Results

Demand parameters are estimated using a GMM framework with moment conditions in Equations 3 and 4. Table 3 reports results from the logit model (Columns 1 and 2) and a random-coefficients logit model (Columns 3 to 5). For both logit and random-coefficients logit demand, the coefficients are positive for battery range, capacity, horsepower, and all-wheel drive, as expected. The coefficient for the BEV dummy variable is negative, indicating that BEVs are less preferable than PHEVs. A plausible reason is that consumers like having gasoline as a backup fuel source.

There are seven endogenous regressors: price and interactions of three measures of charging network quality (Local Levels 2 and 3 and # of City pairs) and two vehicle fuel types (PHEV and BEV). Column 1 shows OLS results, and Column 2 shows results for the IV specification with instruments as described in Subsection 4.2. The first-stage minimum eigenvalue statistic, the analog to the first-stage F-statistic for multiple endogenous regressors, has a value of 59.42, indicating strong instruments (Stock and Yogo (2005)).

The price coefficient can be directly interpreted as a price elasticity due to the log

---

<sup>14</sup>The single event of Tesla introducing an adapter to Chademo stations occurred in April 2015. Without any panel variation in adapter availability, this event is absorbed by the time fixed effect.

specification. The OLS and IV specifications yield similar price elasticities (Columns 1 and 2). A price elasticity of -2.7 from the IV specification is in line with prior literature on the automobile industry (Berry (1994), Berry et al. (1995), and Goldberg (1995)).<sup>15</sup> Station locations and quantities are endogenously chosen by firms, so OLS estimates of the parameters on charging network quality may be biased. Instrumenting for the endogenous regressors increases the precision and magnitude of the coefficients.

Comparing the PHEV and BEV interactions shows that the availability of fast charging stations (Level 3) for both local driving and inter-city travel matters more for BEVs. In contrast, Level 2 charging seems to be more important for PHEVs. A plausible explanation is that for PHEV drivers, gas stations are superior substitutes for Level 3 stations for fast refueling. Therefore, PHEV demand may not respond to Level 3 charging station availability as much as BEV demand. PHEV consumers may see the Level 2 local charging network as a way to opportunistically top up, while BEV consumers see the Level 2 network as poor insurance for running out of electricity because they are so slow. Consumers may suffer from so much range anxiety that they disregard the Level 2 network and only purchase a BEV if they are certain the battery range can cover the majority of their day-to-day needs. Therefore, PHEV demand may be more responsive to Level 2 charging station availability than BEV demand.

Using the price elasticity constructed from the price coefficient and random coefficients (Columns 3 to 5), I compute the markups and marginal costs of vehicles implied by the first-order condition of the firm profit function (Equation 2). Table 4 reports the resulting estimates. I estimate that vehicle markups range from about \$7,500 at the 10th percentile to about \$26,000 at the 90th percentile, in line with gross margins reported by car manufacturers in financial filings. Vehicle marginal costs range from about \$17,000 at the 10th percentile to about \$57,000 per vehicle at the 90th percentile.

I recover charging station costs from the first-order condition of the firms' profit function with respect to charging stations. My cost estimate also includes the discounted present value of the electricity that car manufacturers often offer for free for the first few years of ownership or for the life of the car, but I cannot separate the capital cost and electricity cost components due to data constraints. I estimate that Level 3 charging stations cost about \$10,000 per year on average, implying an upfront,

---

<sup>15</sup>Li et al. (2017) find a much smaller price elasticity of .61 and a charging station elasticity of .84 with a specification that includes product fixed effects. The difference in our estimates is driven by differences in the conditional price variance. The instruments I use to address price endogeneity only require market and time fixed effects to be valid, so I do not include product fixed effects.



discounted present value of \$143,000 per station using a 7% weighted average cost of capital. This estimate of charging station fixed costs is in line with engineering estimates and rumors in the electric vehicle industry that a Level 3 station costs range from \$50,000 to \$150,000.<sup>1617</sup>

## 5 Uniform Charging Standard

I evaluate market outcomes and welfare in the counterfactual policy regime of a unified charging standard for electric vehicles. In each period, firms play a simultaneous-move game as described in detail in Section 3. Firms choose where and how many new charging stations to build, which take one period to complete. Consumers take into account the available charging network when they choose between plug-in vehicles and the outside option to maximize utility. To find an equilibrium of the firms' simultaneous-move game, I simulate firms playing iterated best-response until no firm has any profitable deviations. In each iteration, a firm conditions on the charging station investments built by its competitors and itself in previous iterations to solve its charging station investment problem, which is equivalent to the "fractional knapsack" problem and can be solved with a fast, greedy algorithm (Subsection 5.2).

I present the counterfactual results in three parts in order to build intuition. Readers who are not interested in technical details of the knapsack problem can skip to the final results in Subsection 5.3. First, I compute only demand response to a single charging standard, with the number and locations of charging stations held fixed. Second, taking into account vehicle demand responses to charging stations, firms re-optimize the geographic placement of stations when there is a single standard, given a fixed number of stations. Third, firms optimize over the number of stations in each period, taking into account geographic placement decisions, demand response, and competitors' responses. Throughout the counterfactual analysis, I assume that automakers do not change other vehicle characteristics, including price, whether cars are capable of fast charging at all, and the battery range of each car. Therefore, vehicles are still differentiated products in the counterfactual, with different charging networks depend-

---

<sup>16</sup>Etherington, Darrell. 2013. "Inside Tesla's Supercharger Partnere Program: The Costs And Commitments Of Electrifying Road Transport." *Tech Crunch*, July 26. <https://techcrunch.com/2013/07/26/inside-teslas-supercharger-partner-program-the-costs-and-commitments-of-electrifying-road-transport/>

<sup>17</sup>Holland, Ben. 2014. "Pulling Back the Veil on EV Charging Station Costs." *Rocky Mountain Institute Blog*, April 29. <https://rmi.org/pulling-back-veil-ev-charging-station-costs/>

ing on whether they are capable of fast charging and whether their range covers the distance between pairs of charging stations.

I remain agnostic about how to achieve compatibility. One policy option is to mandate or subsidize R&D for adapters for physical connectors and interoperability of the communication protocols. A stronger policy is the European Union’s rule that any new stations must at least contain a particular standard.<sup>18</sup> All the policy options besides creating adapters would require retrofits of existing stations. My estimated welfare impacts serve as an upper bound on the coordination, R&D, and retrofit costs that society would be willing to pay to achieve compatibility in electric vehicle charging in the U.S., in the confines of my model and its assumptions.<sup>19</sup>

As shown by Small and Rosen (1981) and Williams (1977), the change in consumer surplus in any counterfactual scenario from a comparison scenario is given by:

$$\Delta CS = \int_i \frac{1}{du_i/dy_i} \left[ \left( \ln \sum_{j=1}^J \exp(\delta_r^1 + \mu_{ir}^1) \right) - \left( \ln \sum_{j=1}^J \exp(\delta_r^0 + \mu_{ir}^0) \right) \right] dF(y_i, l_i), \quad (5)$$

where  $du_i/dy_i$  is the marginal utility of income. Social welfare is the sum of consumer welfare and producer profits.

## 5.1 Compatible stations with fixed quantities and locations

This subsection presents two results from simulating access to stations of other standards, holding the quantities and locations of charging stations fixed at the status quo. First, I calculate the increase in consumer surplus from giving Tesla vehicles access to Chademo stations, which can be compared to the retail price of a one-way adapter developed by Tesla. Second, I present the model’s predicted demand response to compatibility across all standards.

Chademo is the dominant and *de facto* standard in Japan. Tesla developed a one-way adapter to give Tesla vehicles access to Chademo stations, likely for the Japanese market, but in March 2015 also released the adapter in the U.S. market. I infer based on a conversation with a Tesla engineer that the adapter took at least two years of development. In the simulation, I assign Tesla vehicles a new charging network consisting of all the existing Tesla stations as well as the Chademo stations. The

---

<sup>18</sup>See Ferwerda et al. (2018) for details on the evolution of charging standards in Europe.

<sup>19</sup>See Simcoe and Farrell (2012) for a discussion of paths toward compatibility.

charging network quality variables for all other vehicles are fixed to the status quo, as are the arrival locations and times of all stations. I then calculate the change in consumer surplus from the change in network access (Equation 5). The retail price of \$450 for a Tesla-to-Chademo adapter is very similar to the model’s prediction of \$426.49 increase in average consumer welfare. Interestingly, Tesla initially launched the adapter for pre-order at \$1000, and then quickly adjusted the retail price to \$450. The retail price need not equal the average consumer surplus change, but this comparison shows that the demand model and parameter estimates predict sensible magnitudes for welfare relative to actual market prices for a limited version of compatibility. Moreover, the retail price for a one-way adapter can give us a sense of the order of magnitude in value we might expect from compatibility.

The gains from compatibility are asymmetric because of differences in battery range. Stations are more useful for vehicles that have the battery range to traverse the gaps between them, as illustrated in Figure 6. Tesla cars, which have about 200 miles of battery range, benefit from access to Combo and Chademo stations because they can easily traverse the distance between all stations. However, other firms’ electric vehicles have at about 80 miles of electric range and cannot traverse the distance between Tesla stations, which are placed 100 to 150 miles apart.<sup>20</sup> Comparing Combo and Chademo networks, cars on the Combo standard gain more because they can access the much larger Chademo network in this counterfactual.

Simulating demand response to a uniform charging standard while holding fixed the quantities and locations of stations shows that sales of plug-in vehicles with fast-charging capability, or those that can use Level 3 stations, would increase by about 26,000 units (17.1%, Table 5). Car brands in the Tesla and Combo coalitions increase sales, but sales of Chademo car brands decrease. The intuition for this result is that the Chademo charging network is an important factor in generating the market shares observed in the data, but in the counterfactual these cars lose the advantage of having more than three times as many charging stations as the cars on other standards (Figure 2). Fast-charge-capable cars steal market share from other plug-in vehicles that cannot fast-charge, though the majority of gains in market share for fast-charge vehicles come from stealing market share from the outside good, the non-plug-in vehicles.

---

<sup>20</sup>Even in Subsection 5.3, when firms re-optimize quantities and locations of charging stations, firms benefit asymmetrically from placing stations closer together. Tesla has no incentive to place their stations closer together for the benefit of its competitors.

## 5.2 Compatible stations with adjustment in locations

This subsection solves the firm location problem for charging station placement for any given quantity of stations. First, I will show that each firm’s charging station allocation problem, conditional on stations already installed by itself and its competitors, maps to a computational problem called *fractional knapsack*. Therefore, a greedy algorithm that chooses locations for stations in order of highest marginal profit gives the optimal solution. Second, I will describe the equilibrium outcomes with three firms locating stations in a static oligopoly game. The equilibrium outcomes are found from firms moving in a predetermined order to play iterated best-response. An equilibrium is reached when no firm has a profitable unilateral deviation.

A single firm’s discrete choice problem of allocating a given  $N$  stations across  $L$  locations is computationally infeasible to solve by enumeration. For example, with  $L = 366$  locations and  $N = 285$  stations to allocate, there are  $\binom{N+L-1}{N} \approx 1.058 \times 10^{192}$  possible arrangements.

Placing  $N$  stations across  $L$  independent locations is equivalent to the fractional knapsack problem. In the knapsack problem, a thief robbing a vault finds  $n$  items. Each item has a value and a weight, both integers. The thief wants to maximize the value of his loot, but he can only carry  $W$  pounds in his knapsack. In the charging station placement problem, firms maximize profits over their station location choices, subject to the constraint of building at most  $N$  stations. The equivalent of an item is the location and how many new stations will be built at that location. The total number of possible items is  $n = L \times N$ , because there are  $L$  total locations and each location can receive up to  $N$  new stations. The ‘knapsack capacity’ of the charging station allocation problem is  $W = N$ . The value of each station is its marginal profit from car sales. The regular, or 0-1, knapsack problem requires that the thief take whole items, while the fractional knapsack problem allows the thief to take parts of items. Both versions of the knapsack problem can be solved in pseudo-polynomial time with a dynamic programming algorithm. The key to mapping the charging station allocation problem to fractional knapsack is that location profits are independent and that stations have uniform weight of 1.

Independence in profits across local markets is given by how charging stations enter the consumer utility function. The demand model specifies that consumers derive utility only from stations inside their own market and from stations that help with inter-city travel. In the model, consumers do not derive utility from any stations

within MSAs that are not in their home city, which could be a reasonable assumption for a variety of reasons, such as not requiring any transit at the destination, avoiding hassle from driving in an unfamiliar city, and using public transit or riding with others. If only charging stations within a consumer’s home market affect utility, then building stations in one market would not affect a firm’s profits in other markets. Therefore, profits from new stations in local networks are independent across markets.

The inter-city network enters the marginal utility of stations in local networks. An additional pair of connected cities changes consumer utility and firm profits from an additional station in every local network. Therefore, to be precise, the charging station allocation problem is equivalent to fractional knapsack conditional on the total number of stations  $N$  and the number of stations allocated to the inter-city network,  $N^{inter}$ . Firms solve the location problem  $N + 1$  times, once for each possible value of  $N^{inter} \in \{0, \dots, N\}$ .

The fractional knapsack problem has the greedy-choice property (Cormen et al. (2009)) and can be solved with a greedy solution. Choosing items in order of highest value-to-weight ratio yields the maximum-value knapsack. The greedy solution in the charging station placement problem is, for each possible number  $N^{inter}$  of stations devoted to the inter-city network, rank the market-quantity combinations in order of decreasing marginal profit and choose the  $N - N^{inter}$  highest. Record total profits for each  $N^{inter}$ . The  $N^{inter}$  and corresponding allocation that gives highest profits is the optimal solution. Allocating stations across local markets is the “inner loop,” and finding the number of stations to allocate to local markets and the inter-city network is the “outer loop.”

Under compatibility, firms locate stations with higher dispersion across markets. This result carries an intuitive interpretation. Consumers derive decreasing marginal utility from additional charging stations of each type. When stations are incompatible, each firm faces a separate decreasing marginal value curve. The first station that a firm builds in a market carries high value, and firms tend to build stations in the same high-profit markets. However, under compatibility, additional stations are worth less if other firms have already built nearby. Therefore, firms build in more markets but fewer stations in each market (Figure 7). The number of markets that have at least one charging station increases from 179 to 339 out of a total of 365 markets, indicating increased spatial dispersion of stations.

### 5.3 Full compatibility counterfactual

The full optimization problem to endogenize both quantities and locations can be solved by nesting the optimal location problem within the optimal quantity problem. Given a number of stations  $N_j$  to allocate, solve the location problem and record the profits. Repeat for every  $N_j \in \{0, \dots, \bar{N}_j\}$ , where  $\bar{N}_j$  is a resource constraint, and choose the  $N_j^*$  and the associated location solution. The resource constraint bounds the search space for computational ease and also reflects managerial or capital constraints that firms may face. I choose the resource constraint to equal the number of stations that I observe firms building in the data. Each period, firms move in iterated best-response to choose optimal quantities and locations until an equilibrium is reached.

Table 6 presents and compares the counterfactual outcomes from each of the three regimes: (1) Incompatible charging standards, (2) Compatible charging standards with private charging investment, and (3) Compatible charging standards with Social Planner charging investment. Over 2011-15, private investment under compatibility results in about \$500 million higher consumer surplus than under incompatibility; the Social Planner achieves about \$3 billion higher consumer surplus than private charging investment. With a compatible charging network, both private investment and social planner investment achieve higher consumer surplus and higher overall producer surplus. However, not all firms are better off with compatibility. Firms originally on the Chademo standard, such as Nissan and Mitsubishi, lose profits under compatibility because they lose one dimension of product differentiation, which is a car with a smaller battery coupled with ample local charging availability. Nissan loses about \$200 million from compatibility.

Compatibility changes the nature of competition among firms, turning investments in charging stations from demand substitutes to demand complements. When a firm builds a station under compatibility, it improves the product quality of its competitors. Therefore, firms have less business-stealing motive to invest in charging infrastructure. The social planner fully internalizes the business stealing effects, and builds about 330 fewer stations (a 17.7% decrease). Firms build about 50 fewer stations (a 2.8% decrease) under compatibility. Notably, all the decrease in private investment comes from Nissan. BMW and Tesla build up to their resource constraint in both regimes.

The number of electric vehicles sold increases by about 100,000 units under compatibility and private investment compared to under incompatible charging standards. About 85,000 more electric vehicles would be sold if the Social Planner were to make

the investment choices instead. The vehicles that have fast-charging capability gain market share overall by stealing market share from the outside option (vehicles of other fuel types) and from other electric vehicles that do not have fast-charging capabilities (“Other Plug-In” in the last row of Table 6). The environmental impacts of a compatibility policy would depend on population density and the electricity fuel mix where consumers substitute to electric from other fuel types. My finding that some manufacturers would lose profits from moving to compatibility may explain why the automotive industry has not standardized electric vehicle charging on its own.

## 6 Conclusion

This paper studies how firms compete in product markets by investing in complementary goods and how firms’ investment incentives change when previously incompatible complementary goods become compatible. The electric vehicle 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.

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 two lines of future work. First, the dynamic incentives in investment intended to influence the equilibrium number of standards remain unexplored. Second, 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 understanding 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's findings supports the argument that in addition to market failures in the upstream innovation stage, other inefficiencies and market failures in downstream product markets can hinder technological change.

## References

- Acemoglu, D., U. Akcigit, D. Hanley, and W. Kerr (2016). Transition to Clean Technology. *Journal of Political Economy* 124(1), 52–104.
- Akerberg, D. A. and M. Rysman (2005). Unobserved Product Differentiation in Discrete-Choice Models: Estimating Price Elasticities and Welfare Effects. *RAND Journal of Economics* 36(4), 771–788.
- Aghion, P., A. Dechezleprêtre, D. Hémous, R. Martin, and J. Van Reenen (2016). Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry. *Journal of Political Economy* 124(1), 1–51.
- Berry, S. (1994). Estimating Discrete-Choice Models of Product Differentiation. *RAND Journal of Economics* 25(2), 242–262.
- Berry, S., J. Levinsohn, and A. Pakes (1995). Automobile Prices in Market Equilibrium. *Econometrica* 63(4), 841–890.
- Berry, S., O. B. Linton, and A. Pakes (2004). Limit Theorems for Estimating the Parameters of Differentiated Product Demand Systems. *Review of Economic Studies* 71, 613–654.
- Blonigen, B. A., C. R. Knittel, and A. Soderbery (2019). Keeping it Fresh: Strategic Product Redesigns and Welfare. *International Journal of Industrial Organization* Forthcoming.
- Borenstein, S. and L. W. Davis (2015). The Distributional Effects of U.S. Clean Energy Tax Credits. In J. R. Brown (Ed.), *Tax Policy and the Economy*, Volume 30, Chapter 6, pp. 191–234. University of Chicago Press.



- Burgelman, R. and D. Schifrin (2011). Nissan’s Electric Vehicle Strategy in 2011; Leading the Way Toward Zero-Emission. Stanford GSB Case SM189.
- Busse, M., J. Silva-Risso, and F. Zettelmeyer (2006, September). \$1000 Cash Back: The Pass-Through of Auto Manufacturer Promotions. *American Economic Review* 96(4), 1253–1270.
- Clinton, B. and D. Steinberg (2016). Providing the Spark: Impact of Financial Incentives on Battery Electric Vehicle Adoption. Unpublished.
- Cormen, T. H., C. E. Leiserson, R. L. Rivest, and C. Stein (2009). *Introduction to Algorithms* (3 ed.). Cambridge, Massachusetts: MIT Press.
- Crawford, G. S., O. Shcherbakov, and M. Shum (2015). The Welfare Effects of Endogenous Quality Choice in Cable Television Markets. CEPR Discussion Paper No. 10793.
- Draganska, M., M. Mazzeo, and K. Seim (2009). Beyond Plain Vanilla: Modeling Joint Product Assortment and Pricing Decisions. *Quantitative Marketing and Economics* 7, 105–146.
- Eizenberg, A. (2014). Upstream Innovation and Product Variety in the US Home PC Market. *Review of Economic Studies* 81, 1003–1045.
- European Commission (2014). Directive 2014/94/EU of the European Parliament and of the Council of 22 October 2014 on the Deployment of Alternative Fuels Infrastructure. <https://eur-lex.europa.eu/legal-content/en/TXT/?uri=CELEX%3A32014L0094>.
- Fan, Y. (2013). Ownership Consolidation and Product Characteristics: A Study of the US Daily Newspaper Market. *American Economic Review* 103, 1598–1628.
- Ferwerda, R., M. Bayings, M. Van derKam, and R. Bekkers (2018). Advancing E-Roaming in Europe: Towards a Single “Language” for the European Charging Infrastructure. *World Electric Vehicle Journal* 9(4).
- Gandhi, A., Z. Lu, and X. Shi (2017). Estimating Demand for Differentiated Products with Zeroes in Market Share Data. [https://www.ssc.wisc.edu/~xshi/research/gandhi\\_lu\\_shi.pdf](https://www.ssc.wisc.edu/~xshi/research/gandhi_lu_shi.pdf).




- Goldberg, P. K. (1995). Product Differentiation and Oligopoly. *Econometrica* 63(4), 891–951.
- Gowrisankaran, G. and M. Rysman (2012). Dynamics of Consumer Demand for New Durable Goods. *Journal of Political Economy* 120(6), 1173–1219.
- Graff Zivin, J. S., M. J. Kotchen, and E. T. Mansur (2014). Spatial and Temporal Heterogeneity of Marginal Emissions: Implications for Electric Cars and Other Electricity-Shifting Policies. *Journal of Economic Behavior & Organization* 107, 248–268.
- Greaker, M. and T.-R. Heggedal (2010). Lock-In and the Transition to Hydrogen Cars: Should Governments Intervene? *The B.E. Journal of Economic Analysis and Policy* 10(1), 1–30.
- Gross, D. P. (2016). The Ties that Bind: Railroad Gauge Standards and Internal Trade in the 19th Century U.S. Harvard Business School Working Paper 17-044.
- Hardman, S., A. Jenn, G. Tal, J. Axsen, G. Beard, N. Daina, E. Figenbaum, N. Jakobsson, P. Jochem, N. Kinnear, P. Plötz, J. Pontes, N. Refa, F. Sprei, T. Turrentine, and B. Witkamp (2018). A Review of Consumer Preferences of and Interactions with Electric Vehicle Charging Infrastructure. *Transportation Research Part D* 62, 508–523.
- Ho, K. (2006). The Welfare Effects of Restricted Hospital Choice in the US Medical Care Market. *Journal of Applied Econometrics* 21, 1039–1079.
- Holland, S. P., E. T. Mansur, N. Z. Muller, and A. J. Yates (2016). Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors. *American Economic Review* 106(12), 3700–3729.
- Holland, S. P., E. T. Mansur, N. Z. Muller, and A. J. Yates (2019). Distributional Effects of Air Pollution from Electric Vehicle Adoption. *Journal of the Association of Environmental and Resource Economists* Forthcoming.
- Holtmark, B. and A. Skonhøft (2014). The Norwegian Support and Subsidy Policy of Electric Cars. Should it be Adopted by Other Countries? *Environmental Science & Policy* 42, 160–168.

- Hortaçsu, A. and J. Joo (2018). Semiparametric Estimation of CES Demand System with Observed and Unobserved Product Characteristics. arXiv:1511.05600v8.
- Houde, J.-F. (2012). Spatial Differentiation and Vertical Mergers in Retail Markets for Gasoline. *American Economic Review* 102(5), 2147–2182.
- Idaho National Laboratory (2015). Plugged In: How Americans Charge Their Electric Vehicles. <https://avt.inl.gov/sites/default/files/pdf/arra/PluggedInSummaryReport.pdf>.
- Ishii, J. (2007). Compatibility, Competition, and Investment in Network Industries: ATM Networks in the Banking Industry. Unpublished.
- Katz, M. L. and C. Shapiro (1985). Network Externalities, Competition, and Compatibility. *American Economic Review* 75(3), 424–440.
- Katz, M. L. and C. Shapiro (1986). Product Compatibility Choice in a Market with Technological Progress. *Oxford Economic Papers* 38, 146–165.
- Knittel, C. R. and V. Stango (2008). Incompatibility, Product Attributes and Consumer Welfare: Evidence from ATMs. *The B.E. Journal of Economic Analysis & Policy* 8(1), Article 1.
- Knittel, C. R. and V. Stango (2011). Strategic Incompatibility in ATM Markets. *Journal of Banking & Finance* 35, 2627–2636.
- Lee, R. S. (2013). Vertical Integration and Exclusivity in Platform and Two-Sided Markets. *American Economic Review* 103(7), 2960–3000.
- Li, S., L. Tong, J. Xing, and Y. Zhou (2017). The Market for Electric Vehicles: Indirect Network Effects and Policy Design. *Journal of the Association of Environmental and Resource Economists* 4(1), 89–133.
- McFadden, D. L. (1974). Conditional Logit Analysis of Qualitative Choice Behavior. In P. Zarembka (Ed.), *Frontiers in Econometrics*, pp. 105–142. New York: Academic Press.
- Michalek, J. J., M. Chester, P. Jaramillo, and C. Samaras (2011). Valuation of Plug-In Vehicle Life-Cycle Air Emissions and Oil Displacement Benefits. *Proceedings of the National Academy of Sciences* 108(40), 16554–16558.

- Nissan Motor Corporation (2012). Nissan Sustainability Report. [https://www.nissan-global.com/EN/DOCUMENT/PDF/SR/2012/SR12\\_E\\_A11.pdf](https://www.nissan-global.com/EN/DOCUMENT/PDF/SR/2012/SR12_E_A11.pdf).
- Nosko, C. (2014). Competition and Quality Choice in the CPU Market. Unpublished.
- Pavan, G. (2015). Green Car Adoption and the Supply of Alternative Fuels. Toulouse School of Economics Working Paper 17-875.
- Petrin, A. (2002). Quantifying the Benefits of New Products: The Case of the Minivan. *Journal of Political Economy* 110(4), 705–729.
- Quan, T. W. and K. R. Williams (2018). Product Variety, Across-Market Demand Heterogeneity, and the Value of Online Retail. *The RAND Journal of Economics* 49(4), 877–913.
- Rantakari, H. (2008). Governing adaptation. *The Review of Economic Studies* 75, 1257–1285.
- Roberts, J. and G. Saloner (2012). Strategy and organization. In R. Gibbons and J. Roberts (Eds.), *Handbook of Organizational Economics*. Princeton University Press.
- Sallee, J. M. (2011). The Surprising Incidence of Tax Credits for the Toyota Prius. *American Economic Journal: Economic Policy* 3, 189–219.
- Sheldon, T. L., J. DeShazo, and R. T. Carson (2017). Designing Policy Incentives for Cleaner Technologies: Lessons from California’s Plug-in Electric Vehicle Rebate Program. *Journal of Environmental Economics and Management* 84, 18–43.
- Simcoe, T. and J. Farrell (2012). Four Paths to Compatibility. In M. Peitz and J. Waldfogel (Eds.), *The Oxford Handbook of the Digital Economy*. Oxford: Oxford University Press.
- Small, K. A. and H. S. Rosen (1981). Applied Welfare Economics with Discrete Choice Models. *Econometrica* 49(1), 105–130.
- Springel, K. (2016). Network Externality and Subsidy Structure in Two-Sided Markets: Evidence from Electric Vehicle Incentives. [https://www.dropbox.com/s/t6iboy3erwdump/kspringel\\_ev.pdf?dl=0](https://www.dropbox.com/s/t6iboy3erwdump/kspringel_ev.pdf?dl=0).

- Stock, J. and M. Yogo (2005). Testing for Weak Instruments in Linear IV Regression. In Andrews, Donald W.K. (Ed.), *Identification and Inference for Econometric Models*, pp. 80–108. Cambridge University Press.
- Sweeting, A. (2013). Dynamic Product Positioning in Differentiated Product Industries: The Effect of Fees for Musical Performance Rights on the Commercial Radio Industry. *Econometrica* 81(5), 1763–1803.
- U.S. Department of Commerce (2016). Automotive Spotlight. <https://www.selectusa.gov/automotive-industry-united-states>.
- U.S. Department of Energy (2014). The History of the Electric Car. <http://energy.gov/articles/history-electric-car>.
- Williams, H. C. W. L. (1977). On the Formation of Travel Demand Models and Economic Evaluation Measures of User Benefit. *Environment and Planning* 9, 285–344.
- Wollmann, T. G. (2018). Trucks Without Bailouts: Equilibrium Product Characteristics for Commercial Vehicles. *American Economic Review* 108(6), 1364–1406.

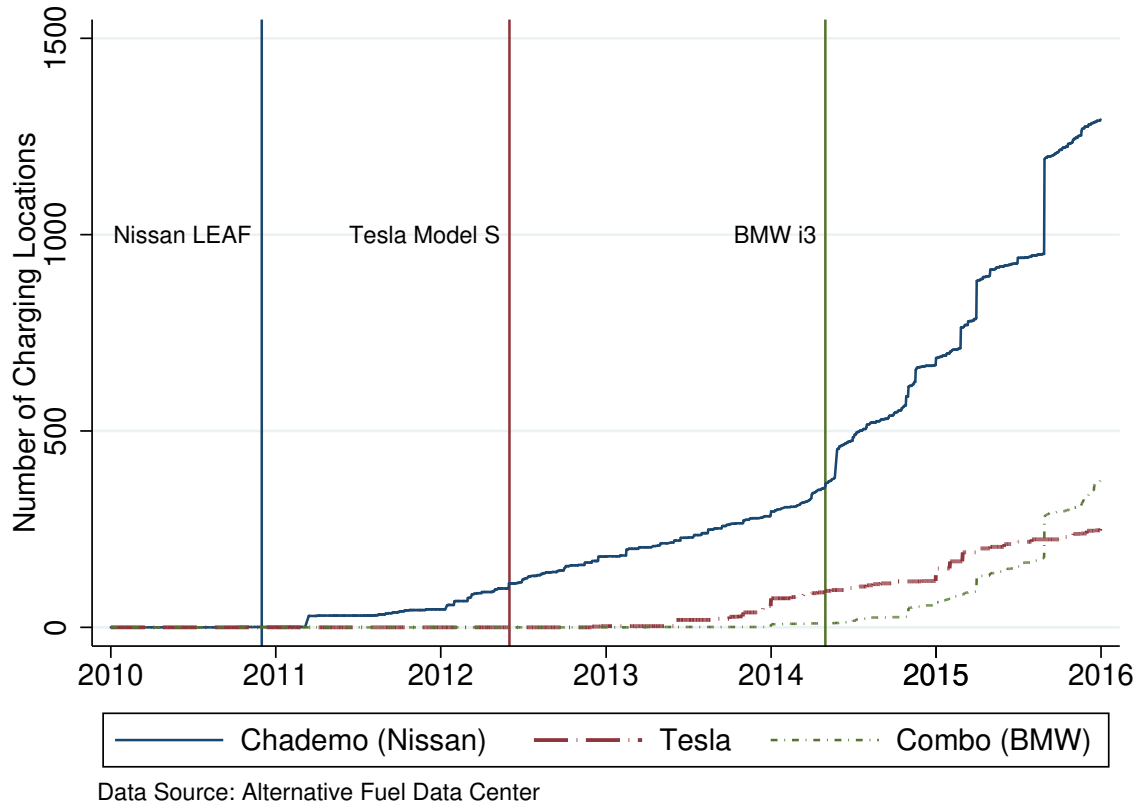
Figure 1: Types of Level 3 (DC, Fast) Charging Standards

Level 3 (DC, Fast) Charging Standards		
		
SAE J1772 Combo	Chademo	Tesla
BMW: i3 GM: Bolt, Spark EV Volkswagen: e-Golf Ford Chrysler Daimler	Nissan: LEAF Mitsubishi: i-MiEV Kia: Soul EV Toyota Peugeot Citroën	Tesla: Model S, X

*Depiction of plug shapes from Alternative Fuel Data Center*

*Notes:* This figure depicts the connectors of each Level 3 electric vehicle charging standard, along with the make and model of cars compatible with each standard as of the end of 2015. Not all electric vehicles on the market are capable of DC fast-charging. The automakers that are listed without vehicle models had pledged support for a particular standard, but did not yet sell vehicles that have fast-charging capabilities as of the end of 2015.

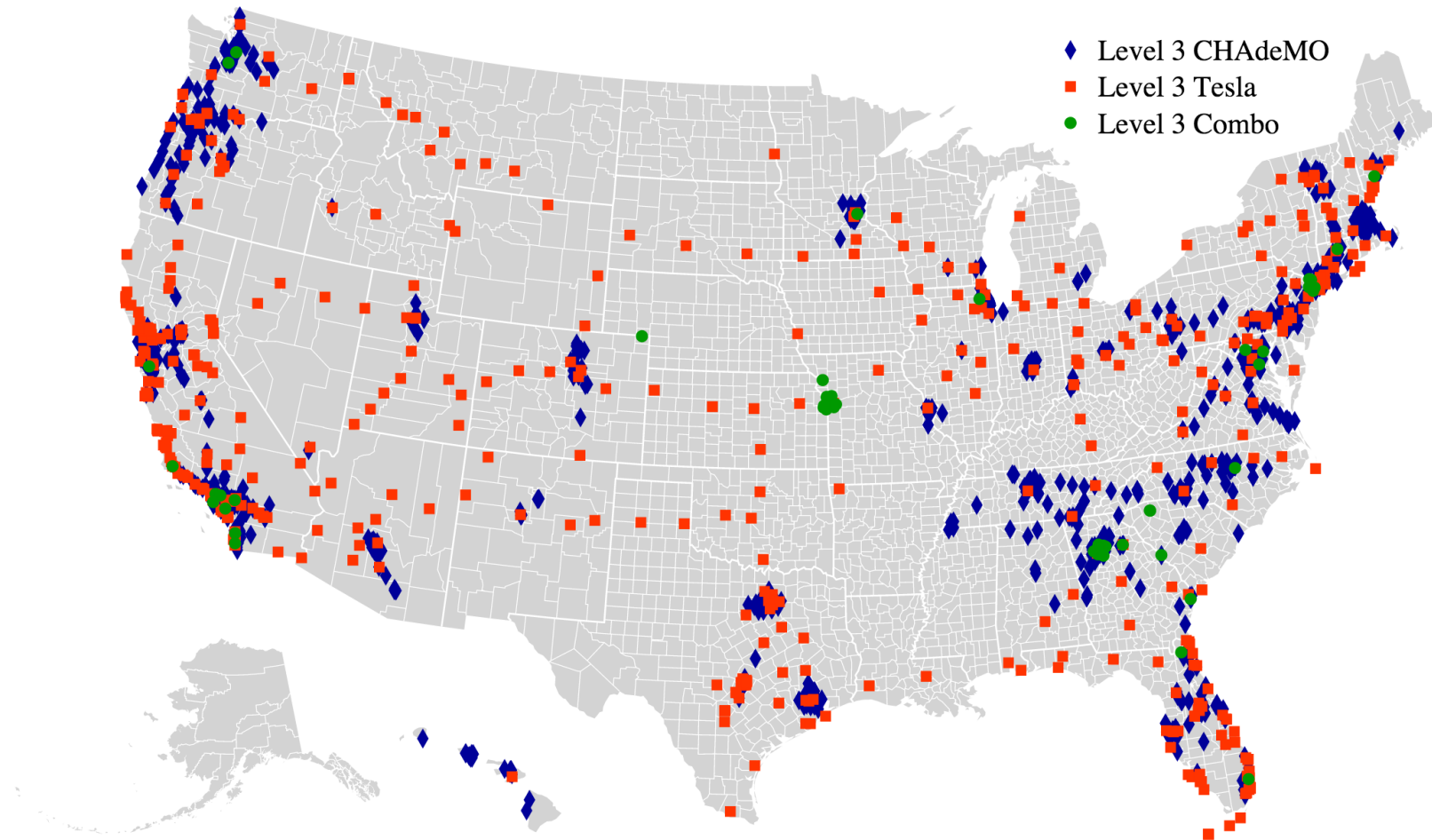
Figure 2: Charging Network Size over Time, by Standard



*Notes:* This figure shows the number of charging locations available over time for each charging standard. 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 of 2010 and began building Chademo stations at the same time.
2. Tesla began deliveries of the Model S in June of 2012 and announced the Tesla Supercharger program three months later, in September of 2012.
3. BMW began deliveries of the i3 in May of 2014 and announced a program to build stations under the Combo standard two months later, in July of 2014.

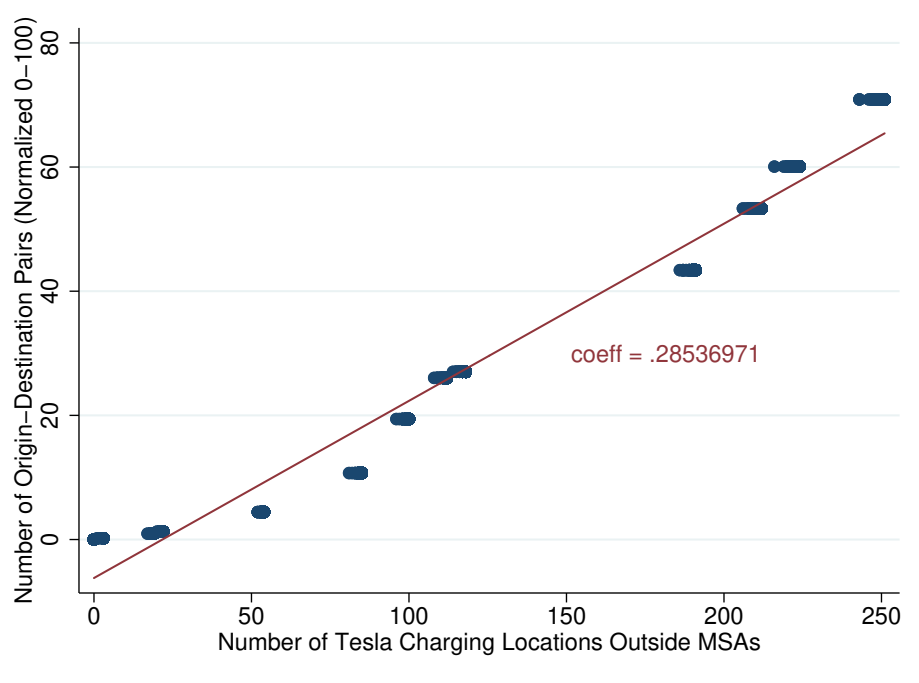
Figure 3: Level 3 (DC, Fast) Charging Locations Plotted on a U.S. Map



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



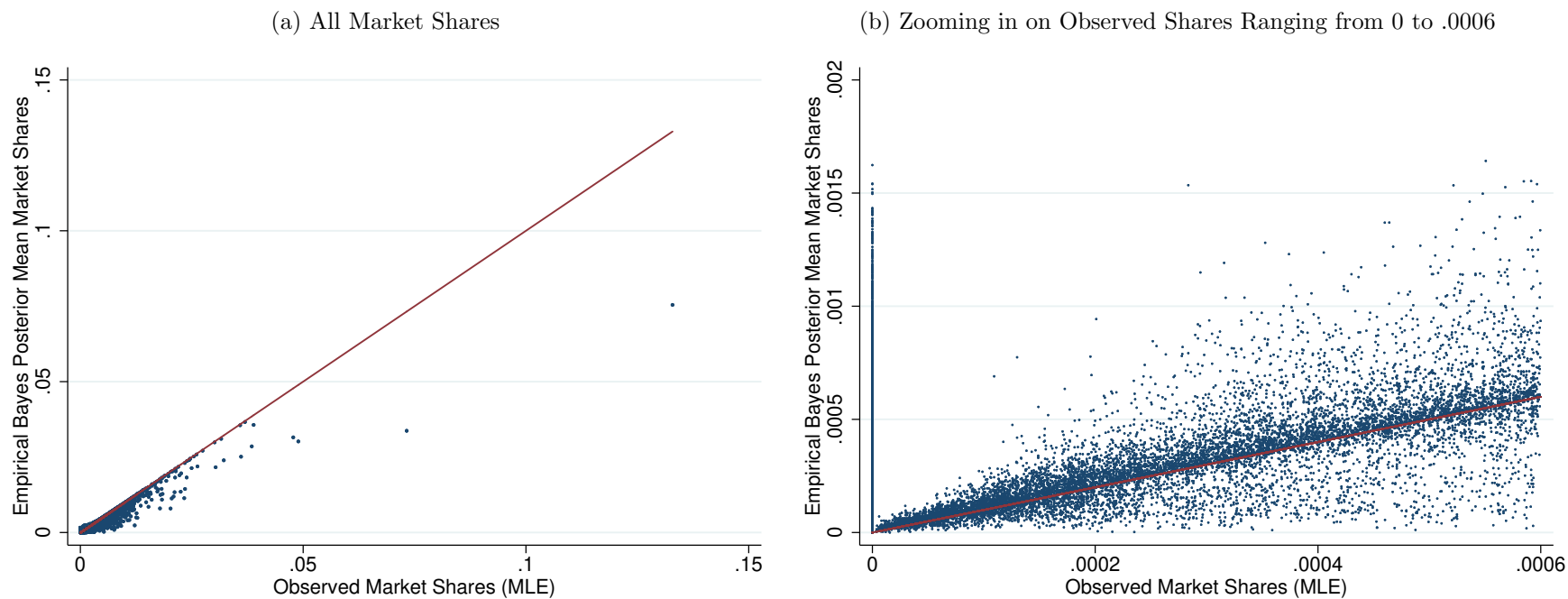
Figure 4: The Number of Connected City Pairs on the Tesla Network



*Notes:* This figure shows the number of city (MSA) pairs that a Tesla car could travel using Tesla’s network ( $y$ -axis), normalized to between 0 and 100, plotted against the number of charging locations available as they were built over time from 2011-2015 ( $x$ -axis).

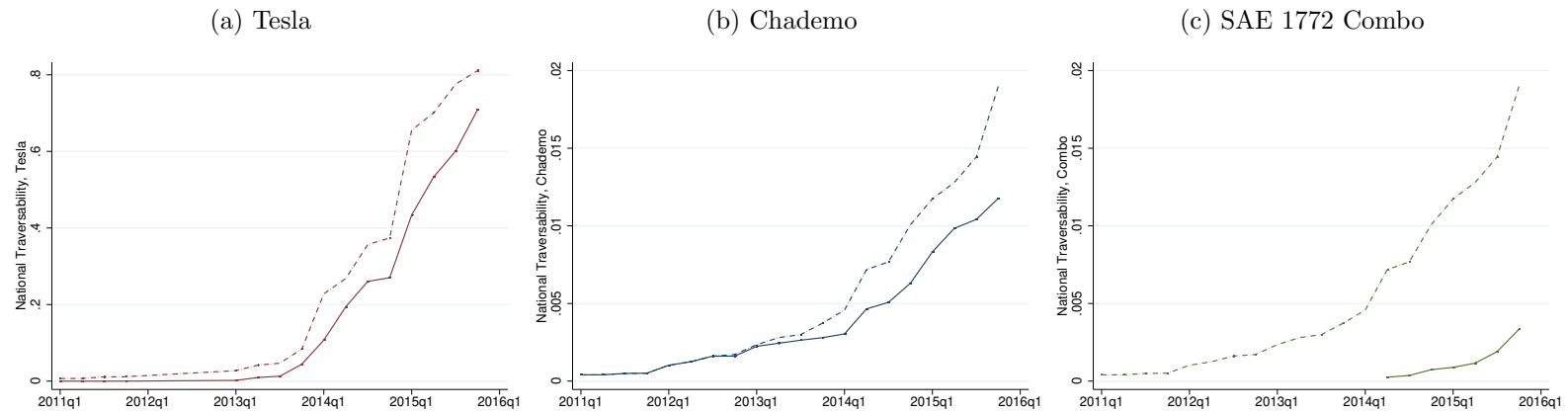
1. In an OLS regression of the number of connected city pairs on the number of charging locations available, the coefficient is about .285, which means an additional pair of cities was connected for about every 3.5 charging locations placed by Tesla.
2. The solid line shows the predicted values from the OLS regression.

Figure 5: Empirical Bayes Posterior Mean vs. Observed Market Shares



*Notes:* This figure plots the empirical Bayes posterior means against the observed market shares. 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.

Figure 6: Counterfactual Traversability of the National Charging Network under Compatibility



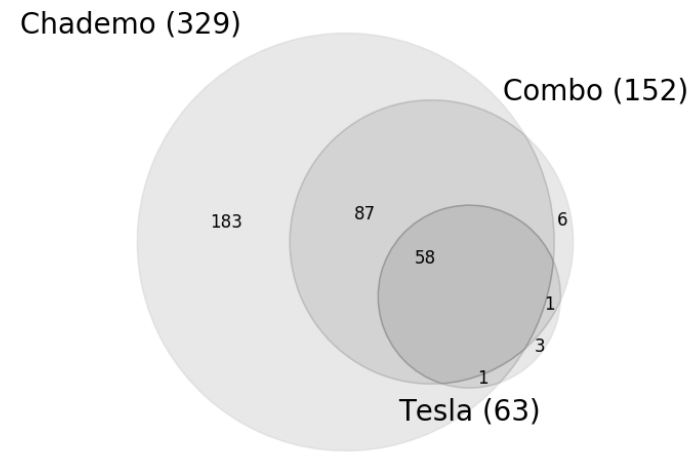
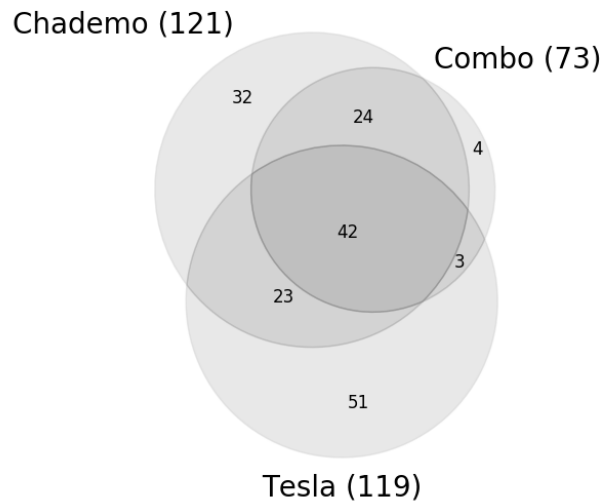
*Notes:* This figure shows the counterfactual traversability (number of city pairs that vehicles can drive) for each of the three standards, holding locations and quantities of stations fixed.

1. Traversability is normalized by the total number of city pairs to between 0 and 1.
2. The solid lines represent traversability in the status quo with 3 incompatible standards, and the dashed lines are the counterfactual traversability with a uniform standard.

Figure 7: Markets with Charging Station Presence from Each Standard (Fixed Number of Stations)

(a) Incompatibility (Status Quo)

(b) Compatibility (Counterfactual)



*Notes:* This figure shows the number of markets that have stations of each standard using Venn diagrams. The left figure depicts the status quo. The right figure depicts compatibility. Under compatibility, all standards are interoperable or the same, so the standards labels merely reference the firms' affiliations in the status quo. In the counterfactual simulations, firms re-optimize locations of stations, holding fixed the number of stations. Under compatibility and with fixed number of stations, firms build in more markets and fewer stations in each market.

Table 1: Evolution of Key Variables, 2011-2015

	2011	2012	2013	2014	2015
Number of markets (MSA)	354	356	347	346	346
Number of EV models	3	6	15	22	27
MSRP of EV models (min)	32,780	29,125	22,995	22,995	22,995
MSRP of EV models (max)	109,000	116,000	102,000	135,700	140,700
EV unit sales	13,542	41,643	93,734	127,699	140,320
Battery range (min)	35	11	11	11	11
Battery range (max)	245	76	139	208	238

*Notes:* This table shows 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.

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

Variable	Mean	Std. Dev.	Min	10%	Median	90%	% Zeros	N
All vehicle sales	13,798.7	28,488.5	202	1,140	3,973.5	37,471	0	40,200
Plug-in sales	20.4	50.2	0	0	1	16	35.7	40,200
2011 plug-in sales	9.5	35.0	0	0	2	18	15.5	1,424
2012 plug-in sales	10.7	49.1	0	0	2	17	23.0	3,910
2013 plug-in sales	11.8	47.8	0	0	1	20	30.8	7,966
2014 plug-in sales	12.0	61.1	0	0	1	20	33.2	11,694
2015 plug-in sales	8.4	42.8	0	0	1	13	45.5	15,206
Observed market share	.00085	.0019	0	0	.00024	.0023	35.7	40,200
Posterior mean share	.00082	.0015	2.78e-9	.000027	.00035	.0020	0	40,200

*Notes:* This table shows summary statistics of vehicle sales, observed market shares, and estimates of empirical Bayes posterior mean market shares. Each observation corresponds to outcomes for an available vehicle model, market (MSA), and quarter, based on data from IHS Automotive from 2011 to 2015.

1. The top panel shows unit sales of all fuel types in the first row, followed by unit sales of plug-in vehicles by year.
2. The bottom panel depicts observed market shares and estimates of empirical Bayes posterior mean market shares.

Table 3: Demand System Estimates

VARIABLES	Logit		Logit with Random Coefficients		
	OLS (1)	IV (2)	RC IV (3)	×Income (4)	×Long Distance (5)
log(Price)	-2.316*** (0.0787)	-2.732*** (0.625)	-2.909*** (0.0248)	-0.166*** (0.0260)	-0.382*** (0.0411)
log(Local Level 2) × PHEV	0.0931*** (0.0177)	0.129*** (0.0295)	0.227*** (.00826)	-0.0818*** (.00771)	0.00136 (.00857)
log(Local Level 2) × BEV	0.0614** (0.0245)	0.0912*** (0.0339)	0.0848*** (0.0105)	-0.00874 (.00968)	-0.0145 (0.0115)
log(Local Level 3) × PHEV	-0.00300 (0.00904)	0.0236** (0.0114)	0.0224* (0.0123)	0.0215 (0.0133)	-0.0139 (0.0133)
log(Local Level 3) × BEV	0.0580*** (0.00776)	0.0671*** (0.00867)	0.0619*** (0.0158)	0.153*** (0.0106)	-0.0460*** (0.0137)
# City pairs × PHEV	-0.234 (0.300)	-0.902* (0.509)	0.014 (0.0447)	0.00128 (0.0109)	-0.00885 (0.00932)
# City pairs × BEV	0.00552*** (0.00155)	0.00524** (0.00267)	-0.0546*** (0.00584)	0.0224*** (0.00393)	0.0410*** (0.00700)
BEV dummy	-1.889*** (0.133)	-2.276*** (0.217)	-2.180*** (0.0243)	-	-
Battery range	0.00760*** (0.00104)	0.00915*** (0.00174)	0.00952*** (0.000153)	-	-
Battery size	0.0302*** (0.00322)	0.0288*** (0.00415)	0.0293*** (0.000219)	-	-
Horsepower	0.00608*** (0.000437)	0.00749*** (0.00265)	0.00796*** (.0000946)	-	-
All-wheel drive dummy	0.631*** (0.0980)	0.989*** (0.231)	1.054*** (0.00549)	-	-
Electricity price	0.00499 (0.0107)	-0.00456 (0.0116)	-0.00909*** (0.000230)	-	-
MSA inc. per cap. (\$1000)	0.0365 (0.0828)	0.215* (0.115)	0.0627*** (.00848)	-	-
Autocorelation of $\xi$ ( $\rho$ )	-	-	0.858*** (0.000230)	-	-
Observations	40,200	35,418	35,418		
R-squared	0.376	0.388	-		
Market FE	✓	✓	✓		
Time FE	✓	✓	✓		
Min. Eigvalue Stat (IV F-stat)	-	59.42	-		

*Notes:* Logit in (1) and (2) are from linear regressions; random-coefficients logit in (3) through (5) are from GMM. (4) shows interactions between product characteristics and household income, and (5) shows interactions with an indicator for whether a household drives more than 60 miles per day. A unit of observation is an available vehicle model, market, and quarter. For (1) and (2), robust standard errors in parentheses. For (3) - (5), standard errors are bootstrapped. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . IVs in (2) include federal and state subsidies that vary within market, over time, and across vehicle models and charging speeds; see Subsection 4.2. Consumer attributes are drawn from the ACS and the NHTS. Charging network quality is separated into three measurements: “Local Level 2” represents slower charging stations inside MSAs, “Local Level 3” represents fast charging stations inside MSAs, and “# City pairs” represents # of cities connected by paths of Level 3 stations.

Table 4: Price Elasticities, Markups, and Marginal Costs

Variable	Mean	Std. Err.			
Own-Price Elasticity	-2.702	0.002			
Level 3 Station Fixed Cost (per year, \$1000)	10.046	0.031			
Variable	Mean	Std. Dev.	10th Pctile	Median	90th Pctile
Price (before subsidies, \$1000)	46.74	26.53	25.17	34.7	96.10
Markup (\$1000)	13.872	8.851	7.577	10.451	25.813
Vehicle Marginal Cost (\$1000)	29.263	15.639	16.900	24.134	56.937

*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.



Table 5: Demand Response to Compatibility (Fixed Station Number and Locations)

Standard	Units Sold in MSAs (2011-2015)			
	Status Quo	Counterfactual	$\Delta$ Quantity	% Change
Chademo	80,673	80,271	-402	-.5
Combo	27,289	31,650	4,361	16.0
Tesla	46,009	68,383	22,374	48.6
Other Plug-Ins	262,956	259,164	-3,792	-1.44
Total Change (Level 3)			26,333	17.1
Total Change (All Plug-Ins)			22,541	5.5

*Notes:* This table shows the consumer demand response to compatibility, with station numbers and locations held fixed. The first three rows show results for vehicles on each of the fast-charging (Level 3) standards. “Other Plug-Ins” are electric vehicles that do not have fast-charge capability.

Table 6: Counterfactual Market Outcomes

	Simulated Counterfactual Outcomes			Difference Across Regimes		
	Incompatible (I) (1)	Compatible (C) (2)	Social Planner (SP) (3)	(C-I) (4)	(SP-I) (5)	(SP-C) (6)
A. SOCIAL WELFARE (\$millions)						
$\Delta$ Social Welfare	-	-	-	2289.998 (1141.106)	4220.684 (638.902)	1930.686 (1361.262)
$\Delta$ Consumer Surplus	-	-	-	490.017 (1146.154)	3104.464 (555.232)	2614.446 (1416.486)
Producer Vehicle Profits	6293.642 (2273.197)	8145.766 (3069.404)	7740.801 (3050.881)	1852.124 (287.890)	1447.159 (417.790)	-404.965 (512.623)
Nissan	1131.595 (922.561)	936.056 (602.007)	852.920 (601.986)	-195.539 (56.665)	-278.675 (127.097)	-83.136 (98.641)
BMW	268.010 (79.694)	936.716 (605.593)	1028.590 (904.527)	668.706 (81.246)	760.580 (127.553)	91.874 (143.222)
Tesla	2161.018 (1359.788)	3416.890 (1700.059)	2982.082 (1582.061)	1255.872 (227.337)	821.064 (229.020)	-434.808 (281.513)
B. NUMBER OF CHARGING LOCATIONS						
Total No. Locations	1868.510 (150.628)	1816.367 (192.070)	1537.571 (382.786)	-52.143 (14.675)	-330.939 (53.401)	-278.796 (52.595)
built by Nissan	1237.510 (150.628)	1185.367 (192.070)	-	-52.143 (14.675)	-	-
built by BMW	380.000 (0.000)	380.000 (0.000)	-	0.000 (0.000)	-	-
built by Tesla	251.000 (0.000)	251.000 (0.000)	-	0.000 (0.000)	-	-
C. EV UNITS SOLD (thousands)						
Total EV Units	488.173 (67.840)	589.649 (144.214)	573.303 (194.166)	101.476 (15.950)	85.130 (29.176)	-16.346 (33.967)
Chademo	127.564 (66.454)	109.711 (45.403)	102.773 (68.634)	-17.853 (4.286)	-24.791 (12.294)	-6.938 (10.773)
SAE Combo	15.670 (3.991)	83.672 (58.325)	86.828 (79.452)	68.002 (8.217)	71.158 (11.395)	3.156 (13.075)
Tesla	83.953 (41.254)	138.351 (63.269)	122.420 (66.109)	54.398 (9.640)	38.467 (9.845)	-15.931 (12.187)
Other Plug-In	260.986 (3.502)	257.914 (9.154)	261.282 (4.250)	-3.071 (0.884)	0.296 (0.689)	3.368 (1.323)

*Notes:* This table presents counterfactual market outcomes with: (1) Three incompatible standards, (2) Compatible standards and private charging investment, and (3) Compatible standards and Social Planner investment. Columns (4)-(6) compare outcomes across regimes. Standard errors are bootstrapped.

# Supplementary Appendix For Online Publication

## A Empirical Bayes Estimator for Market Shares

The empirical Bayes posterior estimate is consistent with the demand model and has advantages over three common methods in the literature for dealing with zero market shares. The first common method is to aggregate to a larger market definition so that zeros are averaged away. Aggregation in this setting 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. 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.

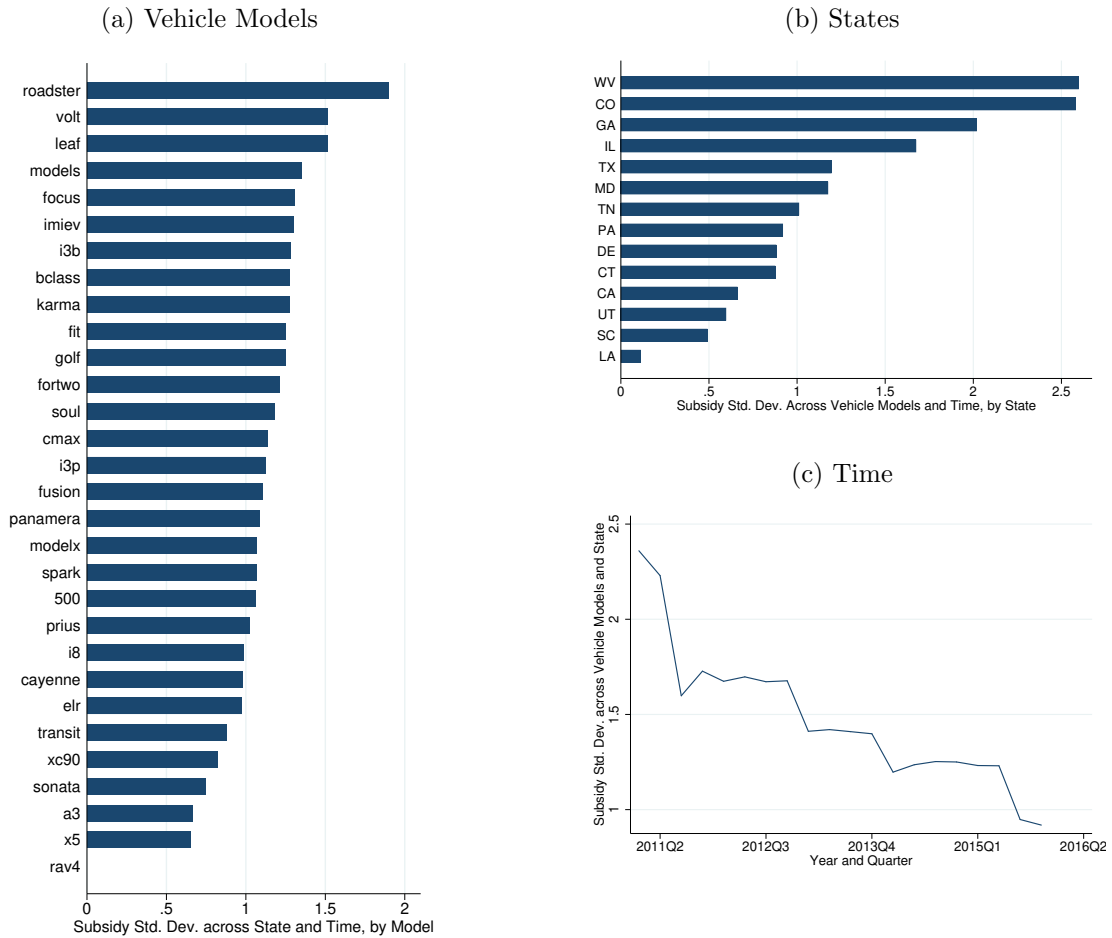
Gandhi et al. (2017) discuss the small and zero market share problem in more detail and present an estimation framework to partially-identify demand parameters. First, they pull market shares away from zero with a Bayesian posterior estimate founded upon Laplace’s rule of succession. Next, they present a moment inequality approach to partially identifying demand parameters. I do not follow their methods for the following reason. The prior from Laplace’s rule of succession is that each product has the same market share, equal to  $\frac{1}{J_{mt}}$ , where  $J_{mt}$  is the number of products in 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 contain more information on purchase probabilities that should be exploited.

Lastly, two other sets of methods are available in the literature for dealing with zero market shares, but are not applicable in my setting. First, Akerberg 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 analysis. Second, Hortaçsu and Joo (2018) present a CES demand system with product characteristics that accommodates zero predicted market shares.

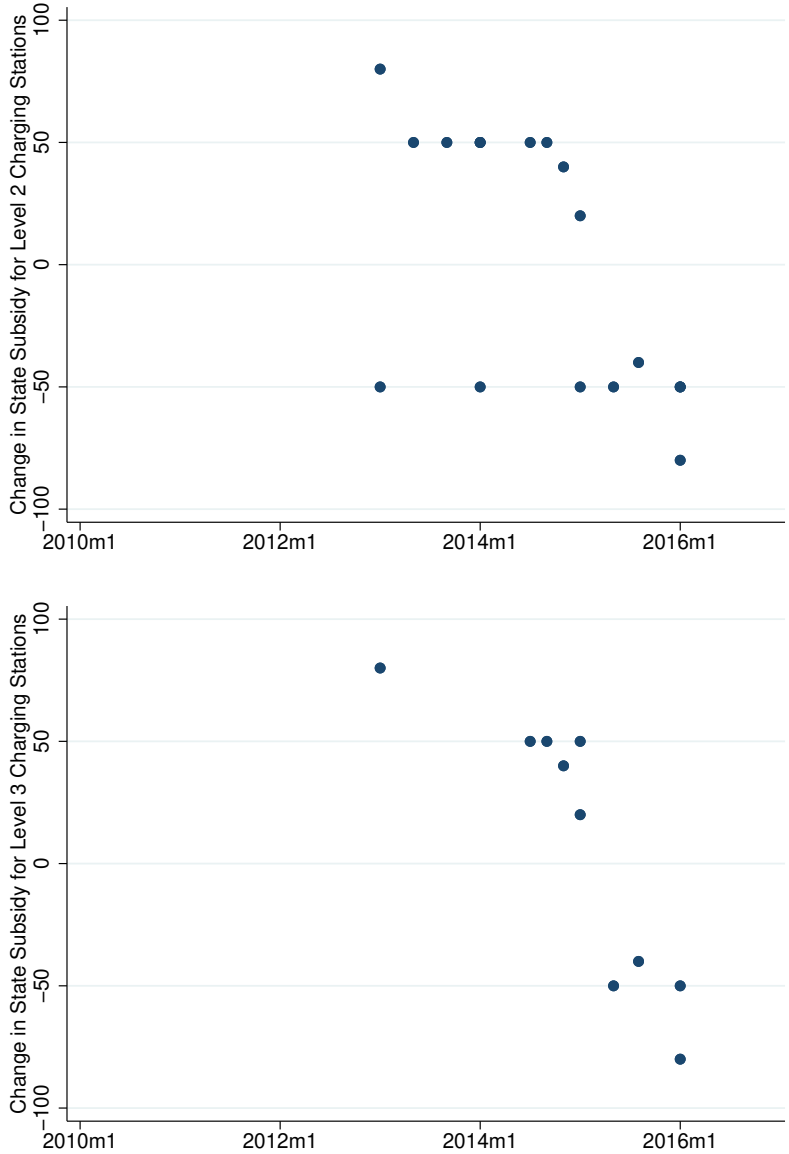
## B State Subsidies

Figure 8: State Subsidies for Plug-In Vehicles across State, Time, and Vehicle Model



*Notes:* This figure depicts variation in state-level subsidies for plug-in electric vehicles from 2011 to 2015. The subsidies are collected from each state's legislative records.

Figure 9: State Subsidies for Charging Stations across State and Time



*Notes:* This figure plots change events (increases and decreases) in state-level subsidies for charging stations from 2011 to 2015. The subsidies are collected from each state’s legislative records. Changes in Level 2 station subsidies are in the top figure, and changes in Level 3 station subsidies are in the bottom figure.