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

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Abstract

Competing standards often proliferate in the early years of product markets, potentially leading to socially inefficient investment. This paper studies the effect of compatibility in the U.S. electric vehicle market, which has grown ten-fold in its first five years but has three incompatible standards for charging stations. I develop and estimate a structural model of consumer vehicle choice and car manufacturer investment that demonstrates the ambiguous impact of mandating compatibility standards on market outcomes and welfare. I estimate my model using U.S. data from 2011 to 2015 on vehicle registrations and charging station investment and identify demand elasticities with variation in federal and state subsidy policies. Counterfactual simulations show that mandating compatibility in charging standards would decrease duplicative investment in charging stations by car manufacturers and increase the size of the electric vehicle market.

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1 Introduction

When firms invest in incompatible complementary goods or technical standards, should the government intervene and mandate compatibility? This question generates fierce policy and antitrust debates in a wide range of industries, from digital markets to manufacturing. 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 for other firms. Therefore, firms may invest too much under incompatibility because private gains from business-stealing do not contribute to social surplus and 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 has grown ten-fold in the number of models and annual unit sales in the five years since its inception in 2011. Electric vehicles attract billions of dollars in government support for the large potential environmental benefits, innovation spillovers, and increase in national energy security. 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 the fastest charging stations to refuel electric vehicles. To the chagrin of many consumers, however, car manufacturers have aligned themselves behind three 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 recently-announced program to build 48 electric vehicle charging corridors on the national highways (White House (2016)) and many utilities across the nation proposing to build charging stations (Mulkern (2016)).

I evaluate the effect of a counterfactual compatibility policy in three main steps. First, I specify a structural model of consumer vehicle purchase behavior and car manufacturer investment in charging stations. Second, I estimate the model using data from
the U.S. electric vehicle market from 2011-2015, which are the first five years of the market. 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.

The mobility of drivers poses a challenge to specifying the relevant charging stations for an individual consumer. As pointed out by Houde (2012), the most useful refueling stations to a consumer may be those that are near their driving paths and destinations rather than their home addresses. 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, timing, and locations. 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. These government subsidies are plausibly exogenous cost shifters due to idiosyncrasies in the policy design and implementation. Additionally, a portion of the charging stations in the dataset are built as part of a Recovery Act program that chose station locations before the beginning of the electric vehicle market. The arrival of these Recovery Act charging stations are plausibly exogenous to unobserved product characteristics and contemporaneous local demand conditions.

I model car manufacturers as competing in static oligopoly. Combining demand parameter estimates and the first-order conditions of the profit function, I recover firms’ markups for vehicles and costs for charging stations, which 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. Allowing consumers to access all three standards while holding charging station supply fixed increases the market share of electric vehicles. Next, firms locate stations with higher dispersion as measured by the number of markets that have any stations when the quantity of stations are held fixed. The intuition for higher spatial dispersion of stations is that consumers have decreasing marginal utility over the charging network. With incompatible standards, the first station that a firm builds is more valuable if
competitors have already built stations nearby. With a combined standard, all firms' investments are useful for all consumers. The first station that a particular firm builds is less valuable if competitors have already built nearby. Lastly, I find that firms do have an incentive to cut back on total station quantities under compatibility, by up to 54% of stations compared to their original investment levels.

This paper contributes to four 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 find considerable gains to consumer welfare (Ho (2006) on insurer-hospital networks) and producer efficiency (Gross (2016) on railroad track widths). However, firms’ incentive to adjust pricing, quality, or investment in response to the compatibility policy may moderate the gains in consumer welfare (Lee (2013) on video game title exclusivity and Knittel and Stango (2008, 2011) on banks and ATM networks). This paper is most similar in methodology to Ishii (2007), who estimates a structural model of consumer and bank behavior to simulate the effect of compatibility (eliminating ATM surcharges) on deposit account competition and ATM network investment. With no ATM surcharges, banks with larger ATM networks lose deposit account market share to smaller banks. All banks would have an incentive to cut back on ATM investment, measured by the profitability of their marginal ATM. This paper extends prior work in the empirical compatibility literature by computing a counterfactual equilibrium investment choice of firms.

Second, this paper contributes to a growing literature on endogenous product positioning. 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, including Wollmann (2016) on commercial trucks, Eizenberg (2014) and Nosko (2014) on CPUs, Sweeting (2013) on radio formats, and Draganska et al. (2009) on ice cream. In some settings, firms face a continuous choice space, such as quality of cable subscription bundles in Crawford et al. (2015) and newspaper characteristics in Fan (2013). Demand estimation typically only recognizes endogeneity of price, assuming that firms choose other characteristics exogenously. However, exogenous arrival of charging stations in the electric vehicle market is difficult to defend firms build new stations each period. Accordingly, I endogenize charging station investment.

Third, this paper contributes a new policy dimension to the academic discourse
on the electric vehicle market. One stream of electric vehicle literature has evaluated the environmental benefits of electric vehicles. Holland et al. (2016a,b), Graff Zivin et al. (2014), and Michalek et al. (2011) evaluate the short-term environmental benefits of electric vehicles. These papers emphasize the importance of geographic variation in electricity generation emissions and conclude that environmental benefits alone in many parts of the U.S. cannot justify current consumer subsidies. However, rapidly changing regulations and advancements in electric vehicles, internal combustion engines, and electricity generation warrant updates in the environmental benefits evaluation. A second stream of electric vehicle literature focuses on the design and impacts of subsidies for electric vehicles and other green technologies (Clinton and Steinberg (2016), Sheldon et al. (2016), Borenstein and Davis (2015), Holtsmark and Skonhoft (2014)). This work finds that consumers do respond to subsidies in their decisions to adopt electric vehicles and other green technologies. The consumers who take up these subsidies tend to be wealthier, and subsidy policies can be designed more carefully to avoid inframarginal consumers. However, these subsidy design papers do not quantify positive adoption spillovers that early adopters may generate and not internalize. Therefore, a third stream of literature evaluates the positive feedback loop between electric vehicle purchases and charging station entry. Li et al. (2016) focuses on the U.S. and Springel (2016) focuses on Norway, and both papers conclude that each side of the market responds positively to each other, and that subsidizing charging station entry is more cost-effective in increasing electric vehicle sales\(^1\). 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 conceptually 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. This paper is the first to study car manufacturer investments in charging stations.

Finally, this paper contributes to a growing literature on directed technical change and climate change policy. Although a market price on environmental damages from emissions and pollution may be part of the first-best solution, political realities and potentially large welfare losses from delaying intervention warrant careful consideration

\(^1\)Pavan (2015) finds that in the market for natural gas cars in Italy, vehicle purchases and refueling infrastructure entry positively respond to each other, and subsidies for refueling stations are more cost-effective for increasing natural gas vehicle adoption. Greker and Heggedal (2010) shows theoretically that for hydrogen cars, a similar positive feedback loop may exist.
of the spectrum of second-best policies. One way to reduce petroleum consumption in transportation is to replace the internal combustion engine with an alternative, such as electric or hydrogen vehicles (Knittel (2012)). Electric vehicles share barriers to market penetration with other alternative fuel technologies, in particular, higher vehicle prices and lack of refueling infrastructure. Lessons in the electric vehicle market can inform policy in other alternative fuel markets. Additionally, 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. However, upstream innovations as measured by patents may not translate into downstream adoption of these technologies (Greaker and Midttømme (2016) and Jaffe et al. (2005)) due to a variety of market failures. This paper examines one possible market failure in the electric vehicle market, the incompatibility of charging standards across different car manufacturers.

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 describes how the model parameters are identified and estimated, and Section 4.3 presents the estimates. Section 5 uses the model estimates to simulate market outcomes under a compatibility policy. Section 6 concludes.

2 The U.S. Electric Vehicle Industry

Institutional details and data availability motivate many aspects of the 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
Since Tesla Motors unveiled the first electric vehicle in 2006, a luxury sports car priced at more than $100,000, automakers have begun to sell models that span a wide range of prices and features. Electric vehicles can be classified into two types: (i) battery electric vehicles (BEVs), which run on only 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 was launched in 2000 as a conventional hybrid, but since 2012 has been available as either a conventional hybrid or 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, like computers, mobile phones, and other consumer electronics.

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 available models in 2011 collectively sold about 14,000 units in U.S. MSAs in 2011. Five years later, the number of models available and annual units sold have both grown 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 the cars in their portfolio. Car manufacturers are also developing BEVs with higher battery ranges and lower prices, such as the Tesla Model 3 and Chevrolet Bolt, both to be launched in 2017. The number of charging locations for electric vehicles has also grown ten-fold, with around 2,000 by the end of 2011 and around 20,000 by the end of 2015.

Battery range and refueling infrastructure are crucial for electric vehicles in providing mobility for their drivers. 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 impacts 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, a 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.

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2Technology 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.
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. Workplaces and owners of shopping malls, restaurants, and hotels have installed Level 2 charging stations as an amenity to their employees and customers. However, four to six hours can still be too long, such as for long-distance trips or for drivers who happen to be out of electricity and need to charge up quickly. 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, direct-current 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, automakers have chosen to invest in the fastest charging stations, the Level 3 chargers. Level 3 charging infrastructure has only been built by automakers, while Level 2 charging infrastructure has been built by employers, business owners, and government programs. Automakers have developed and coalesced around three different charging standards, each not compatible, or interoperable, with the others. In contrast, Level 1 and 2 charging standards are uniform across all vehicle brands. 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 have coalesced behind three mutually exclusive types of Level 3 charging standards (Figure 1).

Car manufacturers only begin 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

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3The 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.
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\(^4\) Combo 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, considered banning all but one standard for charging stations built after 2018 (European Parliament (2013)). Automaker investments in incompatible stations may be socially inefficient for the same reasons that free entry may be excessive. Under incompatibility, new stations are substitutes for existing stations, more so if they are placed geographically closer to each other. The incremental social benefit of a new station may not justify the fixed cost, even automakers find it privately optimal to build.

Optimal policy regarding compatibility is an open empirical question. Incompatibility may lead to wasteful duplication of charging stations. But under a single standard, automakers face diminished investment incentives because of spillover benefits to their competitors. The effect of mandating compatibility across charging standards depends on which force dominates: duplicative investment under incompatibility or free-riding under compatibility. In its final Directive, the EU chose a more moderate approach of requiring that any station 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) rather than banning all but a single standard.

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, reducing geopolitical risk from dependence on petroleum, and innova-

\(^4\)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 direct-current pins under the regular J1772 port, hence the “Combo”. See Figure 1 for a depiction of each standard’s charge ports.
tion spillovers. Government subsidies and ZEV (zero-emissions vehicle) mandates have played a crucial role in the growth of the electric vehicle industry and are therefore important to take into account in this study of charging station compatibility.

Government subsidies for purchase price and charging stations have been designed to address adoption barriers on the demand side, which I use as identifying variation 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 a public refueling infrastructure. Federal income tax deductions 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. Additionally, 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 businesses to build charging stations, ranging from 10% to 50% of costs. The second instrument is the number of new stations in a city that are part of government-funded stimulus projects. In 2009 and 2010, the American Recovery and Reinvestment Act (Recovery Act) allotted $100 million to the Department of Energy to build charging stations. The recipient cities of these government-built stations were chosen before the first electric vehicle, the Nissan Leaf, came to market. Each city was allotted the same number of stations at the beginning of the program and independent of ensuing local electric vehicle sales. The panel variation in Recovery Act charging stations comes from idiosyncratic lags in arrival time from legal and administrative details. Conditional on market and time fixed effects, the Recovery Act stations instrument is arguably uncorrelated with unobservable local preferences.

Zero-emissions vehicle (ZEV) mandates have influenced the growth of the electric vehicle market on the supply side. Designed by the California Air Resources Board (CARB), ZEV mandates require a growing percentage of automakers’ overall sales to be zero-emissions. Under the Clean Air Act, states can choose whether to follow emissions regulations in California. California implements these mandates along with 9 other states. These ZEV regulations are in addition to nationwide emission regulations, such as the CAFE (corporate average fuel economy) standards. Battery electric, plug-in hybrid electric, and hydrogen fuel cell vehicles satisfy ZEV regulations. ZEV regulations have led to the phenomenon of “compliance cars,” which are zero-emissions

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5As of 2016, there are ten states with ZEV mandates: California, Connecticut, Maine, Maryland, Massachusetts, New Jersey, New York, Oregon, Rhode Island, and Vermont.
vehicles that manufacturers only sell in the ZEV mandate states. The ZEV 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 (2% in 2016, 4.5% in 2018, rising to 22% in 2025). 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.

The ZEV mandate affects firms’ decisions through the price of the ZEV credits. Although ZEV credit prices have begun to fluctuate in 2016, the maximum price of $5,000 was binding in the data period of this paper, 2011-2015. I include the value of the ZEV credits as an additive term in the firms’ static profit function. ZEV mandates have influenced the development and availability of electric vehicle models. This paper takes as given the product development process and the car models that are available on the market as a result of either ZEV regulation or other strategic considerations. The model assumes that firms maximize profits over electric vehicles, conditional on selling the car in a particular market and on the price of ZEV credits.

2.4 Data and descriptive statistics

To answer how compatibility in fast-charging stations would impact market outcomes and welfare in the US electric vehicle market, I use 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. Figure 3 shows the spatial arrangement of stations for each standard throughout the U.S.

Fifth, National Household Travel Survey and the American Community Survey provide information on consumer heterogeneity in commuting flows and income.

3 Model

Mandating compatibility in the electric vehicle market may result in different pricing and investment decisions by car manufacturers and consequently, different consumer purchase decisions. I model consumer and firm behavior in order to predict the effect of compatibility on market outcomes and welfare. The demand model is static in that consumers leave the market after their product choice and do not purchase again. Consumers are assumed to be myopic. The demand model 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.

Each period features the following sequence of events:

0. Station investments by firms in 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.

Accordingly, car manufacturers make decisions in two stages. They first choose investments in charging stations, which will arrive in the next period. They next set prices conditional on the charging stations installed in previous periods and consumer demand conditions.

3.1 Consumer demand for cars and charging infrastructure

The main purpose of the consumer choice model is to predict demand response to alternative vehicle prices and charging station availability. 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, an electric vehicle \( r \) by firm \( j \), or the outside good, a non-plug-in car. The demand model is static in that consumers choose myopically, without taking into account future evolution of prices and other product characteristics, and 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 given by:

\[
U_{irmt} = \delta_{rmt} + \mu_{irmt} + \varepsilon_{irmt}. \tag{1}
\]

Consumer utility is comprised of three main terms, the mean utility common to all consumers within a market, \( \delta_{rmt} \), mean-zero individual deviations from mean utility, \( \mu_{irmt} \), and idiosyncratic tastes, \( \varepsilon_{irmt} \).

\[
\delta_{rmt} = \alpha \log(p_{rmt}) + \gamma^S f_{rm}(G_t) + \gamma^L g_{r}(G_t, b_r) + X_{rmt}\beta + \xi_{rmt}, \tag{2}
\]

\[
\mu_{irmt} = y_i(\sigma^y_p \log(p_{rmt}) + \sigma^S f_{rm}(G_t) + \sigma^L g_{r}(G_t, b_r)) + d_i(\sigma^y_d \log(p_{rmt}) + \sigma^S f_{rm}(G_t) + \sigma^L g_{r}(G_t, b_r)). \tag{3}
\]

Consumers derive mean utility, \( \delta_{rmt} \), from price \( p_{rmt} \), charging station access to be detailed later in this section, other characteristics \( X_{rmt} \), and unobservable characteristics \( \xi_{rmt} \). The individual deviations from mean utility, \( \mu_{irmt} \), depend on individual attributes income \( y_i \) and average daily driving distance, \( d_i \). Idiosyncratic tastes \( \varepsilon_{irmt} \) are assumed to be i.i.d. logit. Demand parameters \( \theta \) can be categorized into the ‘linear’ parameters \( \theta_1 \) that enter \( \delta \), and ‘nonlinear’ parameters \( \theta_2 \) that enter \( \mu \). Consumers’ purchase price \( p_{rmt} \) is MSRP less manufacturer discounts and state and federal subsidies:

\[
p_{rmt} = MSRP_{rt} - \text{Manufacturer Discount}_{rt} - \text{State Subsidy}_{rmt} - \text{Fed Subsidy}_r \tag{4}
\]

MSRP and manufacturer discounts are the same across all markets and only vary across 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 pass-through increases with how much consumers know about the subsidies. Equation 4 implicitly assumes that consumers receive the full subsidy, which could be reasonable if consumers know very well the subsidies available to them.

The value of charging networks increases with the number of charging locations and location match quality with consumers’ commuting patterns. Consumers in the model take two types of trips: (i) local travel within the consumer’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 utility terms by the local travel function $f_{rm}(\cdot)$ and intercity travel function $g_{r}(\cdot)$. Empirically, electric vehicle owners charge mainly at home, with about 22% of charge events occurring away from home, according to data from about 5,800 Nissan Leaf and Chevrolet Volt drivers from 2012-13 (Electric Vehicle Project and Idaho National Laboratory). However, the percentage of charging events away from home is not necessarily proportional to importance for electric vehicle adoption. I will infer the importance of charging stations by estimating the electric vehicle purchase 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 locations, and other public locations such as grocery stores or shopping malls (Idaho National Laboratory (2015))\textsuperscript{6}. 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 Level 2 (slower) and Level 3 (fast) charging speeds 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.

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

(5)

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

\textsuperscript{6}See Hardman et al. (2018) for a review of consumer interactions with electric vehicle charging infrastructure.
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. In my model, the commercial core would be the most useful place for a charging location, because it is more likely to be useful to an electric vehicle driver. Next, consider how driving substitutes with public transit. 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 from a low numerator in the population weights $w_c$.

The set of stations $G_t$ may also form a network that enables intercity travel. The intercity travel function $g_r(\cdot)$ counts the number of city pairs that are connected by paths of Level 3 (fast) charging stations. A path of Level 3 charging stations exists if vehicle model $r$ matches each station’s standard, and if the distance from one station to the next station along the route is less than the battery range $b_r$ of the vehicle.

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

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, $g_r(\cdot)$ will be normalized to be between 0 and 1.

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 number of minutes plugged in or 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 all stations to account for an access charge would be absorbed into the constant term in the mean utility. Third, non-pecuniary costs of accessing charging stations - such as search, travel, and hassle costs - are incorporated implicitly by utility increasing in...
charging stations. More charging locations yield lower costs and therefore higher utility.

In contrast to traditional demand estimation with price as the only endogenous characteristic, firms’ investments in charging stations during each period may also be correlated with the unobserved product characteristic, $\xi_{rmt}$. For example, locally targeted advertising is unobserved and may be correlated with firms’ investment choices. A second example of how investment decisions could be correlated with unobservables is if firms 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. Endogenizing charging station choices by car manufacturers contributes to the growing literature on endogenous product characteristics, including Wollmann (2016), Crawford et al. (2015), Eizenberg (2014), and Fan (2013).

Modeling the vehicle purchase decision statically 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). Three features of the electric vehicle market diminish the option value of not purchasing an inside good and waiting for a better version of the inside good to arrive in the future: (i) The battery range of electric vehicles overall from 2011-2015 have not changed meaningfully due to limited advancements in battery technology, (ii) there have been no revolutionary advancements in manufacturing that drastically decrease costs or in new battery chemistries that increase range, and (iii) the new models that have entered later in 2014 and 2015 are similar to the first few models that entered in 2011 and 2012. Consumers who choose a gasoline car for the option value of a better electric vehicle in the future would have had to wait until 2017 for meaningfully different models with longer battery range at mass-market prices, such as the Chevrolet Volt, 2018 model-year Nissan Leaf, and the Tesla Model 3. The most meaningful change in product characteristics, the buildout of charging stations, accrue to all electric vehicles on the same standard. This is in contrast with quality advancements in computers for example, where the improved quality only applies to units purchased later. Therefore, incentives for consumers to wait may not be so high, though I would only be able to formally test the existence of dynamic considerations in the future, after the electric vehicle market has existed for a longer time.

Second, consider the scenario that consumers buy electric vehicles earlier than they
would otherwise because they internalize future improvements to charging networks. Although electric vehicle owners do benefit from charging stations built in the future, I assume that consumers cannot easily move homes, change workplace, or change their driving habits in the short term. The static demand assumption I make can be interpreted as consumers placing all the weight on the present, rather than assuming that consumers don’t expect the charging network to continue to improve.

3.2 Car manufacturer investment in charging infrastructure

This paper focuses on the effect of compatibility policy on car manufacturer investment in electric vehicle charging stations. The model endogenizes firm optimization over the quantity of and locations for electric vehicle charging, conditional on the standards that car manufacturers have chosen to join. 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.

This static model of car manufacturers embeds two implicit assumptions. First, I assume that conditional on the choice of standard and number of stations, 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. Second, 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 2011-2015 is short relative to the product development cycle in the automotive industry overall and particularly in the electric vehicle segment. Although changes in standard gasoline cars may take as little as 3 years for incremental improvements such as fuel efficiency, the earliest electric vehicle models released in the 2011 model year are coming out with major updates only in late 2016, which is after the end of the data period. Blonigen et al. (2013) show that over vehicles of all fuel types, a particular model is redesigned every 4-7 years, and an entirely new model takes even longer.

The profit of firm $j$ in period $t$ from its electric vehicle models $r \in J_{jt}$ is the sum over markups from cars sold minus the cost of charging station investment, given by

$$
\pi_{jt}(G_t) = \left[ \sum_{m} \sum_{r \in J_{jt}} \left( p_{rt} - mc_{rt} + ZEV_{rmt} \right) s_{rmt}(G_t, p_{rmt}; X_{rmt}, \xi_{rmt}, \theta) N_{rmt} \right] - c(a_{jt}),
$$

(7)
where $mc_{rt}$ denotes the marginal cost of producing car $r$ at $t$. Firms maximize profits by choosing $p_{rt}$ and $a_{jt}$, subject to the resource constraint $|a_{jt}| < \bar{N}_{jt}$. The resource constraint can be thought of as coming from managerial capacity constraints and firm capital constraints. Without a resource constraint, firms would build all the stations in the first period, which we do not observe in reality.

Each period, firms simultaneously choose charging infrastructure investment $a_{jt}$ that will arrive at the beginning of next period. They choose the number of stations to allocate to each of 365 local markets and towards connecting city pairs in the national 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,

$$c(a_{jt}) = \kappa |a_{jt}| + \omega_{jt}.$$  \hspace{1cm} (8)

or in other words, that marginal cost of stations is constant. Assuming constant marginal costs could be reasonable because every charging station location could be in a new municipality, with new regulations to learn and local contractors to hire, making learning or economies of scale less likely. The number of stations required to add a new city link is also assumed to be linear, which is born out in the data, as shown in Figure 4. After unobservable product characteristics $\xi_{rmt}$ are realized in each market and period, firms choose car prices to maximize static profits, given the installed charging network $G_t$, characteristics of their own products, and prices and characteristics of other firms’ products. In the model, firms set one price for the country, $p_{rt}$, which is the MSRP minus manufacturer discounts which may vary across time but are the same across regions. I do not observe and therefore do not take into account the region-specific discounts and dealer-specific nonlinear pricing contracts.

Modeling firms as maximizing profits from electric vehicles may be reasonable for two main reasons. First, the organizational structure within firms suggests that the divisions maximize profits over their own division. For example, electric vehicle divisions within firms typically have dedicated leadership and marketing teams. Second, institutional details suggest that firms maximize profits from electric vehicles conditional setting up an electric vehicle division and developing electric vehicle technology. The three firms that are actively building charging stations have prioritized dominance in the electric segment and have zero or very little cannibalization in other segments. 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 are new to the BMW Group (BMW Corporate Communications (2015)). 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 (2011)). Other firms that have not built charging stations by the end of 2015 can be thought of as maximizing profits when setting prices, after taking into account the costs of ZEV regulations in the profit function.

4 Estimation, Identification, and Results

In this section, I describe estimation of the demand and cost parameters and how they are identified. First, 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 estimated. Third, I estimate costs of charging stations from the first order conditions of the firm profit function.

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. The finite sampling process of market shares can lead to zeros despite strictly positive shares predicted by the demand model. 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 empirical market share is an aggregate over the sampled consumers’ multinomial draws. Each market is finite even when the consumer sample consists of all consumers. Coupled with small purchase probabilities, empirical market shares often have zero purchases. Table 2 shows statistics of the unit sales and market shares.
The true purchase probabilities of the multinomial that generated the observed market shares are unknown, but common practice in demand estimation is to use the observed market shares in place of the true purchase probabilities. This implicitly uses the maximum likelihood estimator (MLE). I instead use a parametric empirical Bayes or shrinkage estimator, which generates a posterior estimate of the true purchase probabilities from information in other markets. The posterior estimates are strictly positive and can therefore be inverted as in the Berry (1994) and Berry et al. (1995) framework. 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 fifty markets closest in income per capita.

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 $s_{0 rm}^0$. The purchase probability $s_{0 rm}^0$ are different for each vehicle and market and are drawn from a Beta prior distribution with hyperparameters $\lambda_{1 rm}$ and $\lambda_{2 rm}$. The total number of vehicles purchased is $N_m$. I choose this Beta-Binomial model of market shares for simplicity, though it can be generalized to a Dirichlet-Multinomial. The time subscripts $t$ have been suppressed throughout this subsection for simplicity.

\[
K_{rm} \sim \text{Binomial}(N_m, s_{0 rm}^0) \tag{9}
\]
\[
s_{0 rm}^0 \sim \text{Beta}(\lambda_{1 rm}, \lambda_{2 rm}) \tag{10}
\]

The posterior distribution of the purchase probability is also a Beta distribution, with posterior mean given by equation (12).

\[
\hat{s}_{rm} \sim \text{Beta}(\lambda_{1 rm} + K_{rm}, \lambda_{2 rm} + N_m - K_{rm}) \tag{11}
\]
\[
\hat{s}_{rm} = \frac{\lambda_{1 rm} + K_{rm}}{N_m + \lambda_{1 rm} + \lambda_{2 rm}} \tag{12}
\]

The observed shares, which are the MLE, are

\[
\hat{s}_{rm}^{MLE} = \frac{K_{rm}}{N_m} \tag{13}
\]

The posterior mean replaces the MLE which contains zeros, with $\hat{s}_{rm}$, which is strictly positive. In large samples, the data would dominate the prior.

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

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

(14)

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, \( \hat{s}_{rm} = \frac{\hat{\lambda}_{1rm} + K_{rl}}{N_l + \hat{\lambda}_{1rm} + \hat{\lambda}_{2rm}} \). The bottom panel of table 2 shows statistics of the observed market share and the estimated posterior mean market shares. As expected, the posterior estimates of market shares have lower variance, and all shares are strictly positive.

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 for market shares over other common methods.

4.2 Identification

This paper differs from prior literature in demand estimation by recognizing the endogeneity of a characteristic other than price. 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 stations are exogenous. I first discuss how I identify the price coefficient using variation from government subsidies. The identifying assumption is that for a vector of instruments \( Z_{price} \),

\[
\mathbb{E}[Z_{price} \xi(\theta_2)] = 0.
\]

(15)

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 the sole sources of variation in price. The third set of instruments are BLP instruments, which are the av-
verage characteristics of other products in the market, are relevant instruments 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. Federal plug-in vehicle subsidies vary by car model and are a nonlinear function of the battery capacity. Conditional on product fixed effects or battery capacity of the vehicle, variation in the federal subsidy would be uncorrelated with unobservables $\xi_{rmt}$ if we assume that policymakers set federal subsidies independently from $\xi_{rmt}$. This is a reasonable assumption given that Congress first approved federal plug-in vehicle subsidies as part of an economic stimulus package and has not changed the structure of these subsidies since then.

State plug-in vehicle subsidies vary by state and vehicle model and change over time. Market and time fixed effects control for local factors that do not vary by time, such as local inclinations to be green, and national factors that do not vary across markets, such as national macroeconomic climate and global fuel price shocks. 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, some 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, conditional on controlling for battery capacity and other vehicle characteristics that subsidies condition on.

I next present additional assumptions on the distribution of unobservable characteristics $\xi_{rmt}$ and the instruments that are necessary to identify the charging station coefficients. I assume that unobserved product characteristics $\xi_{rmt}$ evolve according to a first-order autoregressive (AR(1)) process,

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

(16)

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

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

(17)

for a vector of instruments $Z_{station}$. 

21
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 for charging stations that are uncorrelated with demand shocks conditional on market and time fixed effects. The second set of instruments are the number of new stations that are funded by the American Recovery and Reinvestment 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 evolution of the electric vehicle market in each city. Conditional on market and time fixed effects, the number of new stations arriving that are federally funded are due to idiosyncratic permit and build processes uncorrelated with $\nu_{rmt}$. The third set of instruments are the one-period lag of the number of charging stations in a city. In period $t$, car manufacturers choose the quantity and locations of new charging stations to arrive next period conditional on $\xi_{rmt}$. New stations arriving in period $t+1$ are uncorrelated with $\nu_{rmt,t+1}$.

Demand parameters are estimated using a GMM framework with moment conditions in Equations 15 and 17.

### 4.3 Estimation Results

Table 3 reports results from the logit model and a random-coefficients logit model. For both logit and random-coefficients logit demand, the coefficient signs for product characteristics are positive for battery range, capacity, horsepower, and all-wheel drive. The sign on the BEV dummy variable is negative, indicating that BEVs are less preferable than PHEVs. A plausible reason that BEVs are less desirable is that consumers like having gasoline as a backup fuel source with the plug-in hybrids. Columns 4 and 5 of Table 3 display estimates of random coefficients on household income and an indicator variable for whether a household drives more than 60 miles per day. Consumer attributes are drawn from the American Community Survey and the National Household Travel Survey.

There are seven endogenous regressors: three measures of charging network quality that are each interacted with vehicle fuel type, and price. The first-stage minimum

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7The single event of Tesla introducing an adapter to Chademo stations occurred in April 2015. Without any panel variation in adapter availability, this event would be absorbed by the time fixed effect.
eigenvalue statistic, which is the analog to the first-stage F-statistic for multiple endogenous regressors, has a value of 59.42, which indicates that the instruments are strong (Stock and Yogo (2005)). Using the excluded instruments described in Section 4.2 increases the magnitude of the price coefficient from -2.3 to -2.7 (comparison between Column 1 to Column 2). The price coefficient can be directly interpreted as a price elasticity due to the log specification, and a price elasticity of -2.7 is in line with prior literature on the automobile industry. Station locations and quantities are endogenously chosen by firms, so the concern is that OLS estimates of the parameters on charging network quality may be biased upwards, as firms build stations where consumers most prefer them. Instrumenting for the endogenous regressors is shown in Column 2 to increase the precision and magnitude of the coefficients.

Each measure of charging station availability is interacted with a dummy for fuel type, either PHEV or BEV. Comparing the PHEV and BEV interactions shows that availability of Level 3, or fast charging stations matters more for BEVs for both local driving and national long-distance travel. A plausible explanation is that prospective PHEV consumers have a backup gasoline engine and care less about being able to recharge quickly at Level 3 charging stations. In contrast, Level 2 charging is equally important for both PHEVs and BEVs.

With the price elasticity from the demand system, the marginal cost and markups can be computed from the first-order condition of the firm profit function for price. Charging station costs can be recovered from the first-order condition for charging stations. Table 4 reports charging station marginal costs, vehicle markups, and vehicle marginal costs. The discounted present value of charging station marginal costs are about $143,000 if using a 7% discount rate, which can be thought of as a firm’s weighted average cost of capital. This is in line with engineering estimates and rumors in the electric vehicle industry that a Level 3 station costs range from $50,000 - $150,000 (Etherington (2013), Rocky Mountain Institute (2014)). Vehicle marginal costs range from about $17,000 at the 10th percentile to about $57,000 per vehicle at the 90th percentile.

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8Li et al. (2016) find a much smaller price elasticity of .61 and a charging station elasticity of .844. I can find a similar price elasticity using the product fixed effects specification of Li et al. (2016). The difference in estimates for price elasticity is driven by differences in conditional price variance between the characteristics and fixed effects specifications. The price instruments described in 4.2 to address endogeneity only require market and time fixed effects to be valid instruments, so I do not include product fixed effects.
5 Counterfactuals with compatible charging stations

In the first policy experiment, I compare market outcomes and welfare between the observed equilibrium of three incompatible standards and the counterfactual policy regime of a unified standard. The analysis proceeds in three parts. First, I compute the 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. The number of stations that firms build each period are fixed. 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, namely, whether cars are capable of fast charging at all, and the battery range of each car. Therefore, the utility that consumers derive from the combined charging network still varies by car, depending on whether a car is capable of fast charging and whether a car can traverse the distance between charging stations. I also assume that firms set the same prices as observed in the data. Firms choose their station investments separately in this policy experiment.

I remain agnostic about how to achieve compatibility. The compatibility policy could mandate development of adapters or that all stations be retrofitted and built to be multi-standard stations. A stronger policy may be to pick a single standard that is allowed to be built after a certain date, until existing stations and cars under the other standards are phased out. These different ways of achieving compatibility incur different one-time fixed costs of retrofitting existing stations as well as for the cost of stations to be built in the future. The welfare impact that I find serve as an upper bound on the coordination and other costs such that a compatibility mandate would be welfare-improving overall, in the confines of the model and its assumptions and holding other vehicle characteristics fixed. See Simcoe and Farrell (2012) for an exposition on paths toward compatibility.

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

$$\Delta CS = \int \frac{1}{du_i/dy_i} \left[ \left( \ln \sum_{j=1}^{J} \exp(\delta^1_r + \mu^1_{ir}) \right) - \left( \ln \sum_{j=1}^{J} \exp(\delta^0_r + \mu^0_{ir}) \right) \right] dF(y_i, l_i), \quad (18)$$
with $du_i/dy_i$ as the marginal utility of income. Social welfare is the sum of consumer welfare and producer profits.

5.1 Compatible stations with fixed locations and quantities

This subsection presents two results on compatibility and vehicle demand, both holding the supply of charging stations fixed. First, I compare the retail price of a Tesla adapter for the Chademo standard to the change in consumer surplus from the demand model. Second, I present the model’s predicted demand response to compatibility across all standards.

The retail price of $450 for a Tesla-to-Chademo adapter is very similar to the model’s prediction of an increase of $426.49 in average consumer welfare for Tesla vehicle access to Chademo stations. Chademo is the dominant and de facto standard in Japan, with more Chademo charging locations than gas stations, 11 Tesla stations, and 0 Combo stations. Tesla developed a Chademo adapter for the Japanese market, and in March 2015, Tesla released the adapter in the U.S. market. The retail price can be either higher or lower than the average change in consumer surplus, depending on the distribution of consumer preferences. This comparison shows that the demand model and parameter estimates predict sensible magnitudes for welfare relative to actual market prices set by a firm for compatibility. Moreover, the retail price for a one-way adapter can be a reference for the reader regarding the order of magnitude of consumer value for compatibility.

Compatibility only benefits electric vehicles that have the battery range to traverse the gaps between competing standards’ stations. Figure 5 shows the counterfactual changes in national traversability for the vehicles currently under each standard. 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 stations of the other two standards. However, other electric vehicles average 80 miles of electric range and cannot traverse the distance between Tesla stations, which are placed 100 to 150 miles apart. In contrast, Combo and Chademo have cars of similar battery range and stations placed at similar intervals. Compatibility is beneficial to Combo cars because they can access the high number of existing Chademo stations.

Simulating compatibility of all stations and vehicles while holding fixed the locations and quantities, overall sales of the electric vehicle segment increases by approximately 23,000 units over 2011-2015 (Table 5). Car brands in the Tesla and Combo coalitions
increase sales, but sales of Chademo car brands decrease. A plausible explanation is that the Chademo charging network is an important factor in generating the market shares observed in the data, but these brands lose the advantage of having more than three times as many charging stations as each of the other two standards (Figure 2).

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 the spatial allocation problem maps to a computational problem called fractional knapsack, and that a greedy algorithm choosing locations for stations in order of highest marginal profit gives the optimal solution for firms modeled in this paper. Second, I will describe the equilibrium outcomes with three firms locating stations in a static oligopoly game. The equilibrium outcomes are found from firms in a predetermined order playing best response.

A single firm’s discrete choice problem of allocating a given $N$ stations across $L$ locations is computationally infeasible to solve by enumeration. There are $\binom{N+L-1}{N}$ possible allocations, which for $L = 366$ and $N = 285$, is approximately $4.8974 \times 10^{196}$. Fortunately, features from this setting and the model simplifies the problem and decreases the computational burden.

Placing $N$ stations across local markets and the national charging network to maximize profits 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, an item is defined as a location and the $k$th station at that location, $k = 1 \ldots N$. The total number of possible items is $n = L \times N$, and the ‘knapsack capacity’ is $W = N$. The value of each station is the marginal profit from building the station. The 0-1 knapsack problem requires that the thief take whole items, while the fractional knapsack problem allows the thief to take parts of items. The key to mapping this charging station allocation problem to fractional knapsack is that stations have uniform weight of 1. Firms maximize profits over their station location choices, subject to the constraint of building at most $N$ stations.

The equivalence of the station location problem and the knapsack problem relies on independence across the local and national charging networks, which is given by two key features of the demand model. First, the demand model specifies that only
stations inside a consumer’s market and the national network is relevant for demand. Therefore, the profitability of building a charging station in market \( m \) is independent of the investment decision in market \( m' \). Second, the demand model specifies that the local charging network and national charging network enter utility additively and separately. Therefore, the profitability of an additional station in the national charging network is independent of any investment decisions in local markets.

The fractional knapsack problem has the greedy-choice property (Page 425-427, Cormen et al. (2009)). The greedy solution of choosing items in order of highest value-to-weight ratio gives 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 national inter-city network, order the within-city stations in decreasing marginal profit and choose the \( \bar{N} - N_{inter} \) highest. Then, choose the highest-payoff set of inter-city stations and corresponding set of within-city stations, \( (N^*,inter, N^*,within) \). The \( \bar{N} \) represents the resource constraint of the firm for that period. As shown in Figure 4, the number of inter-city links is linear in the number of stations devoted to the national network. Additionally, both versions of the knapsack problem can be solved in pseudo-polynomial time with a dynamic programming algorithm.

I next report equilibrium outcomes, which are found from firms in a pre-determined order playing best-response. An equilibrium is reached when no firm has a profitable unilateral deviation. Under compatibility, firms locate stations with higher dispersion across markets. This result carries an intuitive interpretation. Consumers derive decreasing marginal value 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, with positive spillovers under compatibility, the first station that a firm builds in a market may be of low value if other firms have already built out a network. Firms build in more markets but fewer stations in each market (Figure 6).

5.3 Compatibility with private and social planner investment

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 social welfare than under incompatibility; the Social Planner achieves about $3 billion higher social welfare 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.

Compatibility changes the nature of competition among firms, turning investments in charging stations from demand substitutes to demand complements. Under compatibility, 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, or 17.7% fewer. Firms investing in charging stations to maximize their private surplus, knowing that their competitors can access the stations they build, build about 50 stations fewer, or 2.8% fewer. Notably, all the decrease in private investment comes from Nissan. BMW and Tesla build up to their resource constraint under both incompatible and compatible 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 million more electric vehicles would be sold if the Social Planner were to make the investment choices instead. The vehicles that have fast-charging capabilities overall gain market share, 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 finding that some manufacturers would lose profits from a move toward compatibility may explain why the private market has not moved toward standardization.

6 Conclusion

This paper studies how firms compete by investing in the quality of an important complementary good, and how firms’ investment incentives change when previously incompatible standards 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. A compatibility policy would be welfare-improving even taking into account the cutback in car manufacturer charging station investment.

The framework of this paper can be applied to study other settings where firms' investments have potential spillovers on their rivals, such as in advertising and in innovation and R&D. This paper motivates two lines of future work. First, it would be interesting to study the dynamic incentives in investment intended to influence rivals' choice of standard. 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.

References


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

<table>
<thead>
<tr>
<th>SAE J1772 Combo</th>
<th>CHAdEMO</th>
<th>Tesla</th>
</tr>
</thead>
<tbody>
<tr>
<td>BMW: i3</td>
<td>Nissan: LEAF</td>
<td>Tesla: Model S, X</td>
</tr>
<tr>
<td>GM: Bolt, Spark EV</td>
<td>Mitsubishi: i-MiEV</td>
<td></td>
</tr>
<tr>
<td>Volkswagen: e-Golf</td>
<td>Kia: Soul EV</td>
<td></td>
</tr>
<tr>
<td>Ford</td>
<td>Toyota</td>
<td></td>
</tr>
<tr>
<td>Chrysler</td>
<td>Peugeot</td>
<td></td>
</tr>
<tr>
<td>Daimler</td>
<td>Citroën</td>
<td></td>
</tr>
</tbody>
</table>

*Depiction of plug shapes from Alternative Fuels Data Center*

Notes: The DC fast-charging protocols have distinct connector shapes. Not all electric vehicles on the market are capable of DC fast-charging. The make and model of cars compatible with each protocol is listed, along with automakers who have pledged support for a particular protocol but do not currently sell cars that have fast-charging capabilities. Source of illustrations: Alternative Fuels Data Center.
Figure 2: The number of charging stations for each standard over time

Notes:
1. The number of locations for each charging protocol increases over time.
2. Chademo locations vastly outnumber the other two standards, but a map of these locations in Figure 3 shows a different measure of usefulness.
3. Vertical bars mark when the first cars in each standard were delivered to US consumers and announcements by automakers of their charging station programs shortly afterwards. For each standard, automakers only begin to build stations after they begin to sell vehicles that could use the stations.
   - Nissan begins deliveries of the Leaf in December of 2010 and begins building Chademo stations at the same time.
   - Tesla begins deliveries of the Model S in June of 2012 and announces the Tesla Supercharger program three months later, in September of 2012.
   - BMW begins deliveries of the i3 in May of 2014 and announces a program to build stations under the Combo standard two months later, in July of 2014.
Notes: Visual inspection of the map of existing Level 3 charging stations as of September 2015 hides the fact that Chademo outnumber the other two standards with more than 1000 stations; Combo standard has 380 stations and Tesla has 251 stations. Tesla stations span the U.S. interstate highway system. Chademo and Combo stations cluster near urban areas. Source: Alternative Fuels Data Center of the Department of Energy.
Figure 4: The number of inter-city links are linear in the number of stations

\[
\text{coeff} = 0.28536971
\]
Figure 5: Traversability of the National Charging Network in the Compatibility Counterfactual, Holding Station Locations and Quantities Fixed

Notes:
1. Traversability is defined as the number of city pairs that can be reached using charging stations between them, normalized by the total number of city pairs.
2. The top left panel reproduces the time series of station quantities from Figure 2.
3. The top right and both bottom panels show traversability for vehicles of each standards coalition. The solid line is traversability with incompatibility, and the dashed lines are the counterfactual traversability.
Figure 6: Markets with Charging Station Presence from Each Standard Coalition, Firms Re-Optimize Locations with Quantities Fixed

Notes:
1. The top panel depicts the number of markets with presence by each standard coalition under incompatibility.
2. The bottom panel depicts the simulated number of markets with presence by each standard coalition under compatibility.
3. With the number of stations fixed, firms build stations in more markets and fewer stations in each market.
Table 1: Evolution of Key Variables, 2011-2015

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

Notes:
1. The number of EV models available and unit sales increase ten-fold from 2011-2015.
2. The minimum and maximum MSRP and battery range are quite similar across years.

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

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

Notes:
1. The top panel depicts unit sales of all vehicles (first row) and plug-in vehicles by year for each market.
2. The bottom panel depicts observed market shares and posterior estimates of market shares using empirical Bayes.
3. Products are assumed to be available in a market after the first observed purchase.
4. About 35.7% of model-MSA-quarter observations are zeros.
Table 3: Demand system estimates

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Logit</th>
<th>Logit with Random Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS (1)</td>
<td>IV (2)</td>
</tr>
<tr>
<td>log(Price)</td>
<td>-2.316***</td>
<td>-2.732***</td>
</tr>
<tr>
<td></td>
<td>(0.0787)</td>
<td>(0.625)</td>
</tr>
<tr>
<td>log(Local Level 2) × PHEV</td>
<td>0.0931***</td>
<td>0.129***</td>
</tr>
<tr>
<td></td>
<td>(0.0177)</td>
<td>(0.0295)</td>
</tr>
<tr>
<td>log(Local Level 2) × BEV</td>
<td>0.0614**</td>
<td>0.0912***</td>
</tr>
<tr>
<td></td>
<td>(0.0245)</td>
<td>(0.0339)</td>
</tr>
<tr>
<td>log(Local Level 3) × PHEV</td>
<td>-0.00300</td>
<td>0.0236**</td>
</tr>
<tr>
<td></td>
<td>(0.00904)</td>
<td>(0.0114)</td>
</tr>
<tr>
<td>log(Local Level 3) × BEV</td>
<td>0.0580***</td>
<td>0.0671***</td>
</tr>
<tr>
<td></td>
<td>(0.00776)</td>
<td>(0.00867)</td>
</tr>
<tr>
<td># City pairs × PHEV</td>
<td>-0.234</td>
<td>-0.902*</td>
</tr>
<tr>
<td></td>
<td>(0.300)</td>
<td>(0.509)</td>
</tr>
<tr>
<td># City pairs × BEV</td>
<td>0.00552***</td>
<td>0.00524**</td>
</tr>
<tr>
<td></td>
<td>(0.00155)</td>
<td>(0.00206)</td>
</tr>
<tr>
<td>BEV dummy</td>
<td>-1.889***</td>
<td>-2.276***</td>
</tr>
<tr>
<td></td>
<td>(0.133)</td>
<td>(0.217)</td>
</tr>
<tr>
<td>Battery range</td>
<td>0.00760***</td>
<td>0.00915***</td>
</tr>
<tr>
<td></td>
<td>(0.00104)</td>
<td>(0.00174)</td>
</tr>
<tr>
<td>Battery capacity</td>
<td>0.0302***</td>
<td>0.0288***</td>
</tr>
<tr>
<td></td>
<td>(0.00322)</td>
<td>(0.00415)</td>
</tr>
<tr>
<td>Horsepower</td>
<td>0.00608***</td>
<td>0.00749***</td>
</tr>
<tr>
<td></td>
<td>(0.000437)</td>
<td>(0.00265)</td>
</tr>
<tr>
<td>AWD dummy</td>
<td>0.631***</td>
<td>0.989***</td>
</tr>
<tr>
<td></td>
<td>(0.0980)</td>
<td>(0.231)</td>
</tr>
<tr>
<td>Electricity price</td>
<td>0.00499</td>
<td>-0.00456</td>
</tr>
<tr>
<td></td>
<td>(0.0107)</td>
<td>(0.0116)</td>
</tr>
<tr>
<td>MSA inc. per cap. (ths $)</td>
<td>0.0365</td>
<td>0.215*</td>
</tr>
<tr>
<td></td>
<td>(0.0828)</td>
<td>(0.115)</td>
</tr>
<tr>
<td>$\rho$</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>40,200</td>
<td>35,418</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.376</td>
<td>0.388</td>
</tr>
<tr>
<td>Mkt FE</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Time FE</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Min. Eigvalue Stat (IV F-stat)</td>
<td>-</td>
<td>59.42</td>
</tr>
</tbody>
</table>

Notes: This table reports estimates of parameters in the logit demand model, produced using linear regression. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Table 4: Price elasticity, markups, and marginal costs

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Err. of Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Own-price elasticity</td>
<td>-2.702</td>
<td>0.002</td>
</tr>
<tr>
<td>Charging Station Marginal Cost (ths $)</td>
<td>10.046</td>
<td>0.031</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>10th Pctile</th>
<th>Median</th>
<th>90th Pctile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price (before subsidies, ths $)</td>
<td>46.74</td>
<td>26.53</td>
<td>25.17</td>
<td>34.7</td>
<td>96.10</td>
</tr>
<tr>
<td>Markup (ths $)</td>
<td>13.872</td>
<td>8.851</td>
<td>7.577</td>
<td>10.451</td>
<td>25.813</td>
</tr>
<tr>
<td>Vehicle Marginal Cost (ths $)</td>
<td>29.263</td>
<td>15.639</td>
<td>16.900</td>
<td>24.134</td>
<td>56.937</td>
</tr>
</tbody>
</table>

Notes: This table reports means and standard errors of own-price elasticity and charging station elasticity, as well as means, standard deviations, as well as the 10th, 50th, and 90th percentiles of price, markups, and vehicle marginal cost.
### Table 5: Demand Response to Compatible Stations, Stations Quantities and Locations Held Fixed

<table>
<thead>
<tr>
<th></th>
<th>Actual</th>
<th>Simulated</th>
<th>Quantity Change</th>
<th>% Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chademo</td>
<td>80,673</td>
<td>80,271</td>
<td>-402</td>
<td>-.5</td>
</tr>
<tr>
<td>Combo</td>
<td>27,289</td>
<td>31,650</td>
<td>4,361</td>
<td>16.0</td>
</tr>
<tr>
<td>Tesla</td>
<td>46,009</td>
<td>68,383</td>
<td>22,374</td>
<td>48.6</td>
</tr>
<tr>
<td>Other plug-in car</td>
<td>262,956</td>
<td>259,164</td>
<td>-3,792</td>
<td>-1.44</td>
</tr>
<tr>
<td><strong>Total change in plug-in car sales</strong></td>
<td><strong>22,541</strong></td>
<td></td>
<td></td>
<td><strong>5.5</strong></td>
</tr>
</tbody>
</table>

**Notes:**

1. Firms in the Combo and Tesla coalitions gain unit sales in compatibility when the supply of stations are held fixed. Firms in the Chademo coalition lose unit sales.

2. Sales of plug-in vehicles that are not capable of fast charging decrease. Sales in the plug-in segment increase.
### Table 6: Counterfactual Market Outcomes

<table>
<thead>
<tr>
<th>Simulated Counterfactual Outcomes</th>
<th>Difference Across Regimes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Incompatible (I)</td>
<td>Compatible (C)</td>
</tr>
<tr>
<td>(1)</td>
<td>(2)</td>
</tr>
</tbody>
</table>

#### A. SOCIAL WELFARE ($millions)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th>(C-I)</th>
<th>(SP-I)</th>
<th>(SP-C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔSocial Welfare</td>
<td>-</td>
<td>-</td>
<td>492.583</td>
<td>3109.792</td>
<td>2617.209</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(1146.135)</td>
<td>(555.721)</td>
<td>(1416.737)</td>
</tr>
<tr>
<td>ΔConsumer Surplus</td>
<td>-</td>
<td>-</td>
<td>490.017</td>
<td>3104.464</td>
<td>2614.446</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(1146.154)</td>
<td>(555.232)</td>
<td>(1416.486)</td>
</tr>
</tbody>
</table>

| Producer Vehicle Profits | 6.294 | 8.146 | 7.741 | 1.852 | 1.447 | -0.405 |
| | (2.273) | (3.069) | (3.051) | (0.288) | (0.418) | (0.513) |

<table>
<thead>
<tr>
<th></th>
<th>Nissan</th>
<th>BMW</th>
<th>Tesla</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.132</td>
<td>0.268</td>
<td>2.161</td>
</tr>
<tr>
<td></td>
<td>(0.923)</td>
<td>(0.080)</td>
<td>(1.360)</td>
</tr>
</tbody>
</table>

#### B. NUMBER OF CHARGING LOCATIONS

<table>
<thead>
<tr>
<th></th>
<th>Total No. Locations</th>
<th>built by Nissan</th>
<th>built by BMW</th>
<th>built by Tesla</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1868.510</td>
<td>1237.510</td>
<td>380.000</td>
<td>251.000</td>
</tr>
<tr>
<td></td>
<td>(150.628)</td>
<td>(150.628)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

#### C. EV UNITS SOLD (thousands)

<table>
<thead>
<tr>
<th></th>
<th>Total EV Units</th>
<th>Chademo</th>
<th>SAE Combo</th>
<th>Tesla</th>
<th>Other Plug-In</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>488.173</td>
<td>127.564</td>
<td>15.670</td>
<td>83.953</td>
<td>260.986</td>
</tr>
<tr>
<td></td>
<td>(67.840)</td>
<td>(66.454)</td>
<td>(3.991)</td>
<td>(41.254)</td>
<td>(3.502)</td>
</tr>
</tbody>
</table>

#### Notes:

1. Unsurprisingly, the social planner achieves highest social welfare. Private investment under compatibility achieves about $240 million higher social welfare than under incompatibility.

2. Firms build about 2.8% fewer stations when charging stations are compatible. The social planner internalizes the business stealing effects and builds about 17.7% fewer stations.

3. Producer profits in Panel A and the units of EVs sold in Panel C show that not all firms are better off from compatibility, which may explain why one standard has not emerged from the market. Chademo manufacturers (Nissan and Mitsubishi) would lose profits and market share.
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. (2013) 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 set of methods are available in the literature for dealing with zero market shares, but are not applicable in my setting. First, Ackerberg and Rysman (2005) and Quan and Williams (2014) 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 (2016) present a CES demand system with product characteristics that accommodates zero predicted market shares.

B Federal and state subsidies
Figure 7: Federal subsidies for plug-in vehicles are nonlinear in battery size
Figure 8: State subsidies for plug-in vehicles vary over state, time, and vehicle model.
Figure 9: State subsidies for charging stations vary state and time