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. Compatibility may benefit consumers by providing access to all existing charging stations. However, firms may cut back on their investments because the benefits from one firm's investments spill over to rivals. Firm response in investment may erode consumer gains from compatibility. 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.

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, exogeneity of charging stations in the electric vehicle market is difficult to defend because new stations arrive each period. Accordingly, I use variation from government subsidies to identify demand parameters on price and charging stations.

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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

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[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. Greaker and Heggedal (2010) shows theoretically that for hydrogen cars, a similar positive feedback loop may exist.

potentially large welfare losses from delaying intervention warrant careful consideration 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 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 5 presents the estimates. Section 6 uses the model estimates to simulate market outcomes under a compatibility policy. Section 7 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 Commerce (2016)). 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.[2] 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 3 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,

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

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, 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.[3] 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

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[3]The underlying reason for the lack of entry in building and operating charging stations to sell electricity for profit remains an important question for future research. One plausible explanation is that the size of the electric vehicle fleet does not provide enough revenue relative to the fixed costs of building a charging station.

the launch of fast-charging-capable BEVs, which suggests that firms invest in charging stations in order to boost vehicle sales (Figure 2). Nissan, in partnership with the Tokyo Electric Power Company and other Japanese automakers, developed the Chademo charging standard in 2010, at the same time as the development and release of Nissan's BEV, the Leaf. Tesla Motors announced in September 2012 that it would build a Supercharger network to blanket the U.S., three months after the first delivery of Tesla's BEV, the Model S. Meanwhile, other car manufacturers, working through the Society of Automotive Engineers (SAE), released the specifications of the SAE J1772 Combo 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-

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.[4] 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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[4]As 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 myopic 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

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 the vehicle characteristics, given as:

$$U_{irmt} = \delta_{rmt} + \mu_{irmt} + \varepsilon_{irmt}, \tag{1}$$

with

$$\delta_{rmt} = \gamma^S f(G_t, \bar{l}) + \gamma^L g(G_t, d_r) - \alpha p_{rmt} + X_{rmt}\beta + \xi_{rmt}, \tag{2}$$

$$\mu_{irmt} = y_i(\sigma^S f(G_t, l_i) + \sigma^L g(G_t, d_r) - \sigma^p p_{rmt}). \tag{3}$$

Consumer utility is comprised of three main terms, the mean utility, δ_{rmt}, common to all consumers within a market, mean-zero individual deviations from mean utility, μ_{irmt}, and idiosyncratic tastes, ε_{irmt}.

The mean utility, δ_{rmt} is comprised of a component for mobility, which depends on the vehicle battery range d_r and available stations G_t, $\gamma^S f(G_t, \bar{l}) + \gamma^L g(G_t, d_r)$, price αp_{rmt}, other characteristics $X_{rmt}\beta$, and unobservable characteristics ξ_{rmt}. The individual deviations from mean utility, μ_{irmt}, is comprised of terms for mobility and price, which depend on individual attributes income y_i and location l_i. Idiosyncratic tastes are assumed to be i.i.d. logit.

Consumers' purchase price p_{rmt} is the difference between MSRP and manufacturer discounts as well as state and federal subsidies, given by:

$$p_{rmt} = MSRP_{rt} - \text{Manufacturer Discount}_{rt} - \text{State Subsidy}_{rmt} - \text{Federal Subsidy}_r \tag{4}$$

MSRP and manufacturer discounts are the same across all markets and only vary across time. State subsidies vary across models, markets, and time, and federal subsidies vary across 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 quality of mobility services that consumers derive from an electric vehicle depends on the set of charging stations that have been installed, G_t, each of which has a location, speed, and standard, the location of the consumer, l_i, and the battery range of the electric vehicle, d_r. I split mobility into two types of trips, local travel within the consumer's city of residence and long-distance travel between cities. The function $f(\cdot)$ maps the set of stations and a consumer's location within a city to a measure of local mobility. The function $g(\cdot)$ maps the set of stations and a vehicle's battery range to a measure of national mobility. I define f and g:

$$f(G_t, l_i) = \log(N_{irmt}^{l2}, \text{Number of Level 2 stations in workplace county of consumer } i)$$
$$+ \log(N_{irmt}^{l3}, \text{Number of Level 3 stations in workplace county of consumer } i) \tag{5}$$

$$g(G_t, d_r) = \frac{N_{rt}^{pairs}, \text{Number of traversable city pairs}}{66,430, \text{Total number of city pairs}} \tag{6}$$

When standards are incompatible, f and g only count the Level 3 stations that are on the same standard. In g, a city pair is traversable if Level 3 charging stations spaced less than d_r apart trace a path between the cities that is at most 30% longer than the as-the-crow-flies distance.

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, ξ_{rmt}. For example, locally targeted advertising is unobserved and may be correlated with firms' investment choices. Firms build stations to induce vehicle sales, so they may choose to build in markets with particularly low realizations of ξ_{rmt}. I address the endogeneity of price and investment in charging stations by instrumenting for both variables constructed from government policies 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, despite the durable nature of vehicles and the rapidly changing choice sets in this market. The

details of this setting removes consumers' dynamic consideration of waiting to purchase because they want the better product that will arrive in future periods, as in Gowrisankaran and Rysman (2012). First, the battery range of electric vehicles overall from 2011-2015 have not changed meaningfully due to limitations in battery technology. There have been no revolutionary advancements in manufacturing that drastically decrease costs or in new battery chemistries that increase range. 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. Although consumers benefit from charging stations built in the future, I do not model consumers as forward-looking, given that consumers know and cannot easily adjust their driving needs in the short term. The static assumption can be stated in other words as assuming that consumers only purchase an electric vehicle if the existing charging network serves their present driving needs.

3.2   Car manufacturer investment in charging network

This paper focuses on the effect of compatibility policy on car manufacturer investment in electric vehicle charging stations. The model focuses on firm location choices for stations, conditional on the standards that car manufacturers have chosen to join. These two control variables are part of a dynamic optimization problem driven by firms' expectations of future profits that are not observed in the dataset from 2011-2015. My modeling approach makes two 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. Second, I also assume that vehicle characteristics other than price and charging stations evolve according to an exogenous 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, such as improvements in 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 function over electric vehicles in each period is given by:

$$\pi_{jt}(G_t) = \sum_m \sum_{r \in \mathscr{J}_{jt}} (p_{rt} - mc_{rt} + ZEVcredit_{rmt})s_{rmt}(G_t, p_t; x_t, \xi_t, \theta)M_{mt} - c(a_{jmt}^{l3}, a_{jt}^{pairs})$$

(7)

Each period, firms choose the locations of new charging stations that will arrive next period. They choose the number of stations to allocate to each local market and towards connecting city pairs in the national market, for a total of 366 choice variables. After unobservable product characteristics ξ_{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. Firms set one price for the country. The price that firms receive for a vehicle, p_{rt}, is the MSRP less manufacturer discounts.

The model specifies that firms choose their charging station investment and set prices to maximize profits over electric vehicles. Most firms sell vehicles of other fuel types, including gasoline, hydrogen, natural gas, and diesel. Firms may not be maximizing profit over the electric segment if they are concerned about cannibalizing sales in other segments. For example, Petrin (2002) describes delay in Ford's development of a minivan due to potential cannibalization of Ford's station wagon sales.

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 dedicated leadership and marketing groups. 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 and Identification

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 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_{rm}^0. The purchase probability s_{rm}^0 are different for each vehicle and market and are drawn from a Beta prior distribution with hyperparameters λ_{1rm} and λ_{2rm}. 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 subscripts have been suppressed throughout this subsection for simplicity.

$$K_{rm} \sim \text{Binomial}(N_m, s_{rm}^0) \tag{8}$$

$$s_{rm}^0 \sim \text{Beta}(\lambda_{1rm}, \lambda_{2rm}) \tag{9}$$

The posterior distribution of the purchase probability is also a Beta distribution, with posterior mean given by equation (11).

$$\hat{s}_{rm} \sim \text{Beta}(\lambda_{1rm} + K_{rm}, \lambda_{2rm} + N_m - K_{rm}) \tag{10}$$

$$\hat{s}_{rm} = \frac{\lambda_{1rm} + K_{rm}}{N_m + \lambda_{1rm} + \lambda_{2rm}} \tag{11}$$

The observed shares, which are the MLE, are

$$\hat{s}_{rm}^{MLE} = \frac{K_{rm}}{N_m} \tag{12}$$

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, $l \in \mathscr{B}_m$. The parameters of the Beta prior, λ_{1rm} and λ_{2rm}, are estimated from maximizing the log of the likelihood over the outcomes in the markets that form the priors.

$$f(K_{rl}, l \in \mathscr{B}_m | \lambda_{1rm}, \lambda_{2rm}) = \prod_{l \in \mathscr{B}_m} \binom{K_{rl}}{N_l} \frac{\Gamma(\lambda_{1rm} + \lambda_{2rm})\Gamma(\lambda_{1rm} + K_{rl})\Gamma(N_l - K_{rl} + \lambda_{2rm})}{\Gamma(\lambda_{1rm})\Gamma(\lambda_{2rm})\Gamma(N_l + \lambda_{1rm} + \lambda_{2rm})} \tag{13}$$

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I estimate a pair of hyperparameters $\hat{\lambda}_{1rm}$ and $\hat{\lambda}_{2rm}$ for each vehicle, market, and period, and construct the posterior mean estimate of purchase probabilities, $\hat{s}_{rm} = \frac{\hat{\lambda}_{1rm} + K_{rm}}{N_m + \hat{\lambda}_{1rm} + \hat{\lambda}_{2rm}}$. 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.

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.[5]

4.2   Consumer demand

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},

$$\mathbb{E}[Z^{price}\xi(\theta_2)] = 0. \tag{14}$$

I use three sets of instruments for price that are plausibly uncorrelated with unobservable characteristics ξ_{rmt}. First, federal 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 is uncorrelated with unobservables ξ_{rmt}. Second, state subsidies vary by state and time. I argue that state subsidies are uncorrelated with demand shocks ξ_{rmt} conditional on market and time fixed effects, which 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. Third, BLP instruments, which are the average 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 ξ_{rmt} given the assumption that the other product characteristics arrive as part of an exogenous development process.

I next present additional assumptions on the distribution of unobservable charac-

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[5]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. However, demand for vehicles are more sensibly modeled as single-unit purchases, as in the discrete-choice logit and random coefficient logit models.

teristics ξ_{rmt} and the instruments that are necessary to identify the charging station coefficients. I assume that unobserved product characteristics ξ_{rmt} evolve according to a first-order autoregressive (AR(1)) process,

$$\nu_{rm,t}(\theta_2) = \xi_{rm,t}(\theta_2) - \rho\xi_{rm,t-1}(\theta_2), \tag{15}$$

that ν_{cmt} are mean zero, independent across vehicle models r, markets m, and time periods t, and that

$$\mathbb{E}[Z^{station}\nu(\theta_2)] = 0 \tag{16}$$

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

I use three sets of instruments for charging stations that are plausibly uncorrelated with innovations in demand unobservables, ν_{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 ν_{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 ξ_{rmt}. New stations arriving in period $t+1$ are uncorrelated with $\nu_{rm,t+1}$.

Demand parameters are estimated using a GMM framework with moment conditions in 14 and 16.

5 Estimation Results

5.1 Demand parameters

Table 3 reports results from a logit model, which is the version of the demand model setting σ parameters from the demand model to zero. The estimates are produced using linear regression as in Berry (1994). For both the OLS and IV specifications

in Columns 1 and 2, 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.

There are seven endogenous regressors: three measures of charging network quality that are each interacted with vehicle fuel type, and price. The instruments are strong, with a first-stage minimum eigenvalue statistic of 59.42. Stock and Yogo (2005) explain that the minimum eigenvalue statistic is the relevant statistic for multiple endogenous regressors, and that the F-statistic is the minimum eigenvalue statistic when there is only one endogenous regressor. Stock and Yogo (2005) also provide tables of critical values. 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.[6] 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.

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[6]Li 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. Therefore, including product fixed effects may not be appropriate.

5.2 Firm costs

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. Table 4 reports the markups and marginal costs.

Moreover, charging station costs can be recovered from the first-order condition for charging stations. Consumers in the model consider the stock of all charging stations when choosing their vehicle, so a newly-built station contributes toward profits in every time period thereafter. Therefore, an estimate of the cost of a charging station is the discounted present value of the stream of profits. The static marginal profit for a Chademo station and a Combo station is $4,827 and $6,648, respectively. These estimates imply charging station costs of $96,540 and $132,960, respectively, with a 5% discount rate. This is very close to the 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)).

6 Policy Experiment 1: 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 numbers of stations in each period, taking into geographic placement decisions and demand response. 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 a 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:

$$\Delta CS = \int_i \frac{1}{du_i/dy_i} \left[\left(\ln \sum_{j=1}^J \exp(\delta_r^1 + \mu_{ir}^1) \right) - \left(\ln \sum_{j=1}^J \exp(\delta_r^0 + \mu_{ir}^0) \right) \right] dF(y_i, l_i), \ (17)$$

with du_i/dy_i as the marginal utility of income.

6.1 Compatible stations with the same 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 distri-

bution 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 4 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 6). 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).

6.2   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 kth 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 corresponding greedy solution in the charging station placement problem is to order the market-stations in decreasing marginal profit and choose the N highest. 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 de-

creasing 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 5).

6.3 Compatible stations with adjustment in locations and quantities

Compatibility changes the nature of competition among firms, turning investments in charging stations from demand substitutes to demand complements. Therefore, previously profitable investments may no longer be desirable by firms in the compatibility counterfactual. Simulations show that firms have incentive to reduce the number of stations they build by up to 54% in some periods. Over all periods 2011-2015, simulations show that total number of stations built by car manufacturers decreases by 335, or 17% compared to investment quantities in the data. Nevertheless, unit sales of electric vehicles still increase from compatibility. The average gain in consumer surplus from compatibility is about $2,000. Total welfare change per period from summing over changes in consumer surplus for all consumers and producer surplus is $60.6billion. Although this number may seem quite large, the automotive industry accounts for about $500billion of annual US GDP.

7 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

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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.

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

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

Depiction of plug shapes from Alternative Fuel 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. Image source: Alternative Fuels Data Center.

Figure 2: The number of charging stations for each standard over time

Data Source: Alternative Fuel Data Center
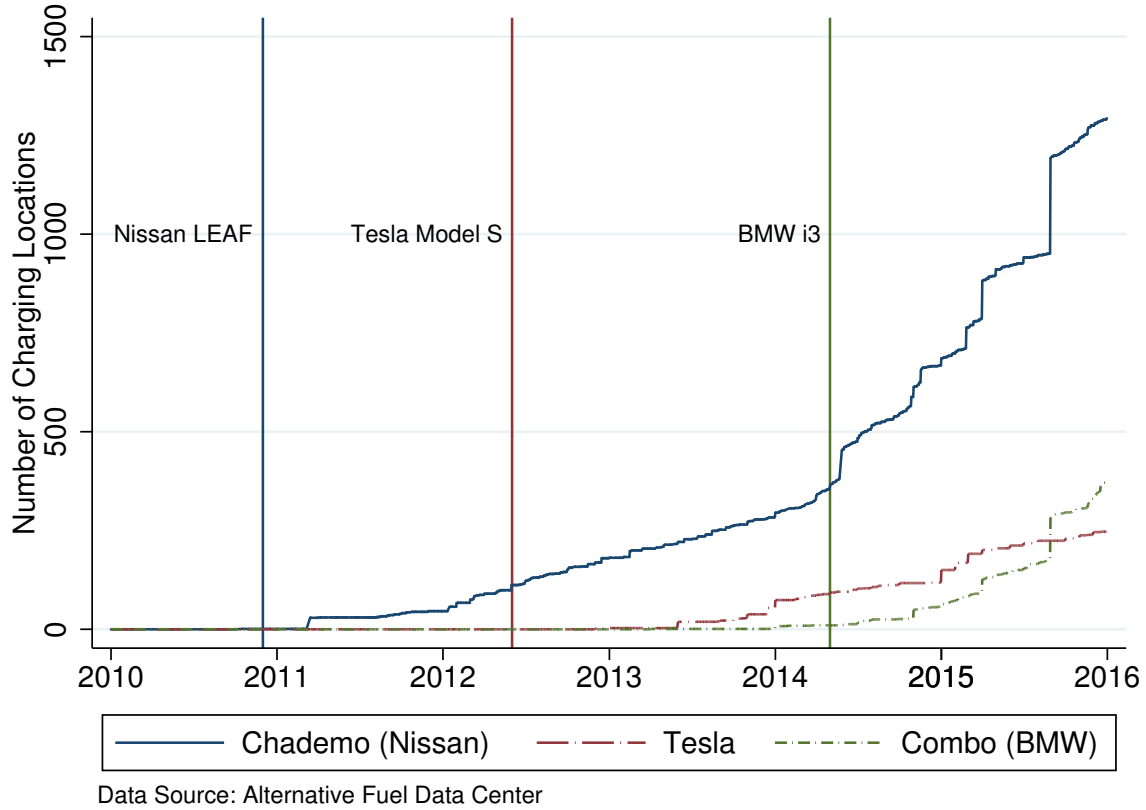
Notes:

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.

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

♦ Level 3 CHAdeMO
■ Level 3 Tesla
● Level 3 Combo
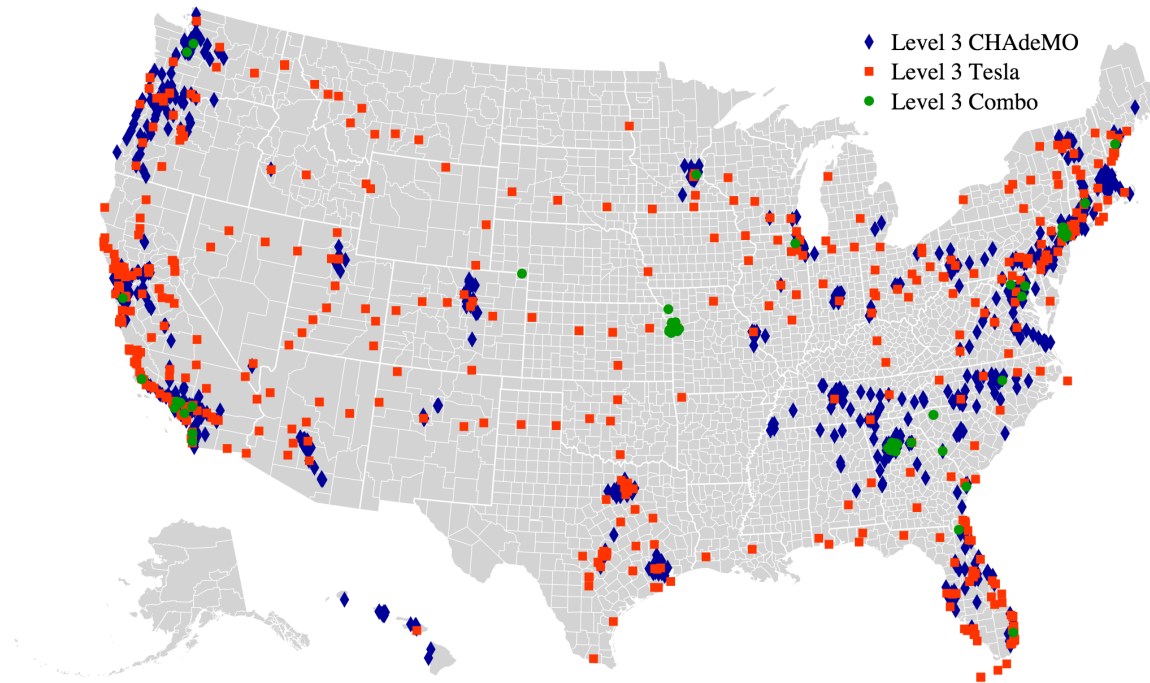
Notes: Visual inspection of the map of existing Level 3 charging stations as of September 2015 hides the fact that Chademo outnumber the other two standards with more than 1000 stations; Combo standard has 380 stations and Tesla has 251 stations. Tesla stations span the U.S. interstate highway system. Chademo and Combo stations cluster near urban areas. Source: Alternative Fuels Data Center of the Department of Energy.

Figure 4: Traversability of the National Charging Network in the Compatibility Counterfactual, Holding Station Locations and Quantities Fixed
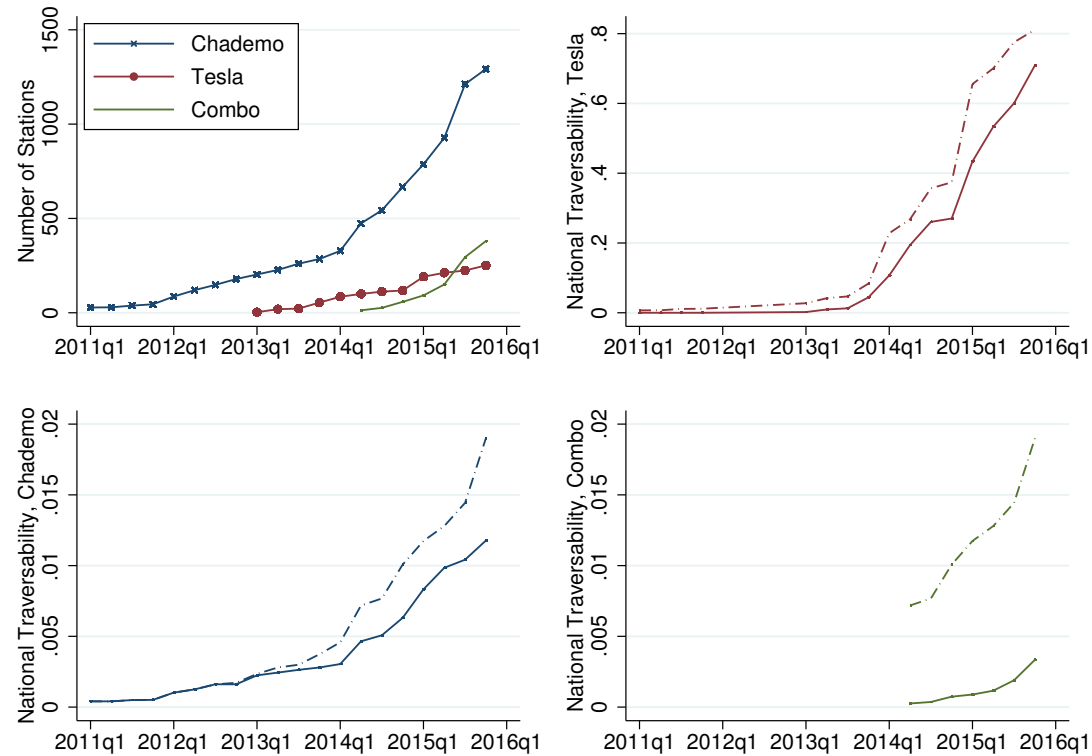
Notes:

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 5: Markets with Charging Station Presence from Each Standard Coalition, Firms
Re-Optimize Locations with Quantities Fixed

Chademo (121)
Combo (73)
32
24
4
42
3
23
51
Tesla (119)

Chademo (329)
Combo (152)
183
87
6
58
1
3
1
Tesla (63)
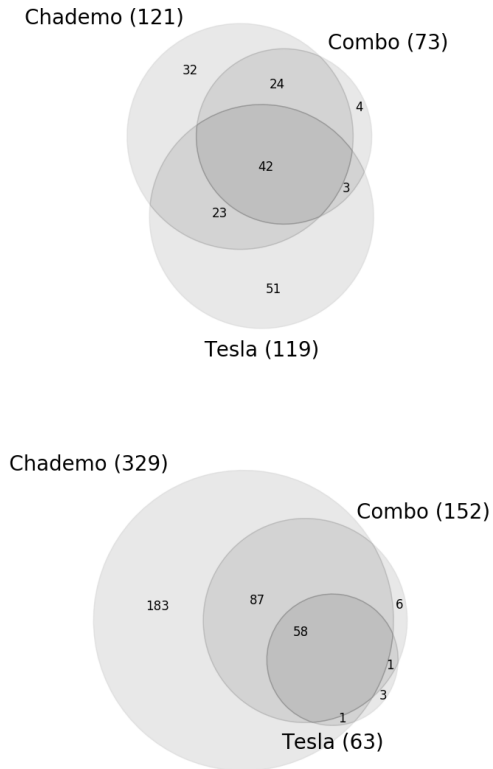
Notes:

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

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

Notes:

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

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

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. Model-level unit sales display 35.7% zero market shares.

Table 3: Logit demand estimates

VARIABLES	(1) OLS	(2) IV
log(Price)	-2.316***	-2.732***
	(0.0787)	(0.625)
log(Local Level 2) × PHEV	0.0931***	0.129***
	(0.0177)	(0.0295)
log(Local Level 2) × BEV	0.0614**	0.0912***
	(0.0245)	(0.0339)
log(Local Level 3) × PHEV	-0.00300	0.0236**
	(0.00904)	(0.0114)
log(Local Level 3) × BEV	0.0580***	0.0671***
	(0.00776)	(0.00867)
# City pairs × PHEV	-0.234	-0.902*
	(0.300)	(0.509)
# City pairs × BEV	0.00552***	0.00524**
	(0.00155)	(0.00267)
BEV dummy	-1.889***	-2.276***
	(0.133)	(0.217)
Battery range	0.00760***	0.00915***
	(0.00104)	(0.00174)
Battery capacity	0.0302***	0.0288***
	(0.00322)	(0.00415)
Horsepower	0.00608***	0.00749***
	(0.000437)	(0.00265)
AWD dummy	0.631***	0.989***
	(0.0980)	(0.231)
Gasoline price	0.00458	-0.0485
	(0.0698)	(0.0766)
Electricity price	0.00499	-0.00456
	(0.0107)	(0.0116)
MSA income per capita (USD '000)	0.0365	0.215*
	(0.0828)	(0.115)
Observations	40,200	35,418
R-squared	0.376	0.388
Mkt FE	X	X
Time FE	X	X
Minimum Eigvalue Stat (IV F-stat)		59.42

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, marginal costs, and markups

Variable	Mean	Std. Dev.	10%	Median	90%	# Obs.
Price (before subsidies) (USD '000)	46.74	26.53	25.17	34.7	96.10	250
Own-price elasticity	-2.73	.63	–	–	–	–
Markup (USD '000)	16.87	9.56	9.243	12.523	34.755	250
Marginal cost (USD '000)	29.27	16.57	15.922	21.662	60.184	250

Notes: This table reports means, standard deviations, as well as the 10th, 50th, and 90th percentiles of Price, Own-price elasticity, Margins, and Marginal Cost. The total number of observations are 250 model-quarters over 2011-2015. There are 30 models and 20 periods, throughout the sample period, but the total number of observations is not $30 \times 20 = 600$ because not all models are available for all periods.

Table 5: Demand Response to Compatible Stations, Stations Quantities and Locations Held Fixed

	Units Sold in MSAs (2011-2015)			
	Actual	Simulated	Quantity Change	% Change
Chademo	80,673	80,271	-402	-.5
Combo	27,289	31,650	4,361	16.0
Tesla	46,009	68,383	22,374	48.6
Other plug-in car	262,956	259,164	-3,792	-1.44
Total change in plug-in car sales		22,541		5.5

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: Change in Market Outcomes in Compatibility Counterfactual

	Δ Stations	Δ Plug-in Sales	$\overline{\Delta CS}$	ΔPS
Location Adjusts, Quantity Adjusts	-335	63,171	$2,338	$733,791

Notes: This table presents changes in the number of stations built by car manufacturers, unit sales of plug-in vehicles, average consumer surplus, and total producer surplus under compatibility. Total welfare change sums over consumer surplus for all consumers and producer surplus, for a total welfare gain of $60.6billion per period.