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TECHNOLOGY ADOPTION AND CRITICAL MASS: THE CASE OF THE U.S. ELECTRIC VEHICLE MARKET*

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The interdependence between electric vehicle (EV) adoption and charging station deployment could lead to multiple equilibria. Under certain market conditions, the issue of critical mass arises and a market failing to overcome this hurdle would revert to a no-adoption outcome. Using panel data of EV sales and charging stations across U.S. Metropolitan Statistical Areas (MSA's), we find that more than half of the MSA's face critical mass constraints and that a subsidy policy targeting these critical-mass constrained MSA's could be much more effective in promoting EV adoption than the current uniform policy.

I. INTRODUCTION

In many new technology markets, a consumer's benefit from adopting the primary good depends on the availability of complementary goods while an investor's benefit from supplying the complementary goods depends on the installed base of the primary good. The interdependence between the demand for the primary good and the supply of the complementary goods is referred to as an indirect network effect in the literature. Examples of this phenomenon include computer hardware and software, CD players and CD's, video game consoles and games, and eReaders and eBooks. Inherent in this type of market is the coordination problem whereby one group of market participants tends to wait for the other group to act before taking their own action. This can lead to multiple equilibria with different levels of technology adoption (see Caillaud and Jullien [2003]). When a market exhibits two positive-adoption equilibria, the low-adoption equilibrium characterizes the

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critical-mass constraint in that if the market fails to overcome this hurdle, the adoption level will revert to zero in the long run, resulting in the failure of the technology. Therefore, understanding the nature of market equilibrium and the issue of critical mass is crucial for understanding the diffusion path of the new technology and for designing effective policies to promote the technology.

This paper studies the market for electric vehicles (EV's).[1] This market is characterized by indirect network effects in that the demand for EV's depends on the availability of publicly-accessible charging stations and the supply of charging stations depends on the installed base of EV's. Our objective is to study the adoption of this new technology by taking into account such indirect network effects and to explore the policy implications of the critical mass issue. The EV technology is considered the future of fuel technology in passenger vehicles.[2] The diffusion of electric vehicles together with a clean electricity grid can be an effective combination in reducing local air pollution, greenhouse gas emissions and oil dependency. Policy makers in the U.S. and other countries are employing a variety of policies and allocating significant resources to promote the EV technology. Nevertheless, the diffusion and the long-term survivability of the technology are not well understood. To what extent and for how long the government should support the technology hinges on important aspects of the market, including indirect network effects and the properties of market equilibrium.

We first develop a stylized theoretical model to examine the diffusion of EV's by incorporating the interdependence between consumers' adoption of EV's and investors' supply of charging stations. We show that there exists three types of self-fulfilling equilibria in the steady state under reasonable assumptions about the magnitude of the indirect network effects, the distribution of consumer tastes and the profitability of charging station investment. When the EV price is sufficiently high, no-adoption is the only long-run outcome and, in this case, the market will eventually revert to no-adoption no matter where it starts. When the EV price is sufficiently low, no-adoption and high-adoption are the two equilibria, where the no-adoption equilibrium is unstable and the high-adoption equilibrium is locally stable. In this case, a slight deviation from the origin would propel the market into a trajectory towards the high-adoption equilibrium. Interestingly, when the EV price is in a certain range, there exist three equilibria where the no-adoption and high-adoption equilibria are locally stable and the

[1] Electric vehicles use electricity that is obtained from an external power source during a charging period and stored in rechargeable batteries, as opposed to conventional gasoline-powered vehicles, which use an internal combustion engine.

[2] A report on the global outlook of vehicle technology by the International Energy Agency predicts that by 2050, over half of all passenger vehicles on the road will be electric vehicles. Hydrogen vehicles (not yet mass-produced) will account for the majority of the remaining vehicles. See *https://www.iea.org/publications/freepublications/publication/EV_PHEV_Roadmap.pdf.*

low-adoption equilibrium is unstable. In this case, the low-adoption equilibrium characterizes the critical mass constraint in that if the market fails to overcome this hurdle it will revert to no-adoption in the long run.

To bring the model to the data, we parameterize our theoretical model and derive a simultaneous system of two equations: an EV demand equation that quantifies the effect of the availability of charging stations on EV adoption; and a charging station supply equation that quantifies the effect of the installed base of EV's on the deployment of charging stations. Our estimation is based on a rich data set of quarterly new EV sales by vehicle model and the number of charging stations across 354 U.S. Metropolitan Statistical Areas (MSA's) from 2011 to 2013. We use the instrumental variables to address simultaneity between the adoption of EV's and the supply of charging stations as well as the endogeneity issue due to the correlation between vehicle price and unobserved product attributes.

We find statistically and economically significant indirect network effects in the EV market across various specifications. Our analysis of the long-run equilibrium suggests that more than half of the MSA's face the critical-mass constraint. To examine the impact of the current federal subsidy policy on EV adoption, we simulate EV sales in the steady state for each MSA under different policy scenarios. Our simulation results suggest that the current federal policy would increase the total EV adoption by 21.4% in the steady state. More importantly, a subsidy policy of equal budget size that tailors the subsidy amount per EV based on the equilibrium property of the MSA (e.g., providing a subsidy sufficient for the MSA to surpass the critical mass constraint) could be much more effective in promoting EV adoption than the current policy of uniform subsidy per EV across MSA's.

Our study directly contributes to the following three strands of literature. First, our study fits into the rich literature on markets with indirect network effects. This literature is built on theoretical works such as Katz and Shapiro [1985, 1986] and Farrell and Saloner [1985]. Many empirical studies on indirect network effects have emerged in the past two decades. These studies mostly focus on markets that can be characterized by a classic software-and-hardware paradigm including the CD players and CD's market by Gandal *et al.* [2000], the yellow page market by Rysman [2004], the electronic payment system by Gowrisankaran and Stavins [2004] and Ackerberg and Gowrisankaran [2006], and the video game market by Clements and Ohashi [2005]; Lee [2013] and Zhou [2017].

Second, our study also contributes to the literature on the critical mass issue in network industries. Most previous studies derive theoretical or conceptual explanations of why some markets exhibit the critical mass phenomenon. Markus [1987] shows that the underlying production function and consumer heterogeneity lead to critical-mass constraints in media markets. Cabral [1990] shows that the 'catastrophe points' occur only if the network effects are sufficiently strong. Economides and Himmelberg [1995] shows that the critical mass of a network is independent of market structure. Evans and Schmalensee [2010] conceptually illustrate that the critical-mass hurdle depends on the nature of network effects, the dynamics of consumer behavior, and the distribution of customer tastes. Greaker and Heggedal [2010] theoretically demonstrate that critical-mass constraint exists when hydrogen technology is moderately more costly than the current fossil fuel technology, and thus policy makers should seek to coordinate the market to the equilibrium with high hydrogen car usage. The only empirical analysis on the critical mass issue that we are aware of is Grajek and Kretschmer [2012] who empirically identify the conditions for the existence of critical mass in the global cell phone market using country-level data. Different from the cell phone market with direct network effects, the EV market exhibits indirect network effects and hence our analysis uses different modeling and empirical specifications. In addition, the EV market is subject to various government policies across countries and we pay particular attention to the policy implications of the critical mass issue.

Third, our study adds to the emerging literature on the EV market and the alternative fuel vehicle market in general. Langer and McRae [2014] study the importance of the network of E85 fueling stations in consumers' decision to adopt flex-fuel vehicles using rich individual driving and fueling station data. Shriver [2015] finds significant network effects in the demand for flex-fuel vehicles and the entry decision of ethanol fuel retailers. Holland *et al.* [2016] find considerable variation in the environmental benefit of electric vehicles across geographic areas due to variations in the fuel source of electricity generation and demonstrate that geographically differentiated subsidy policy is superior to the current federal uniform subsidy policy. Li *et al.* [2017] offer the first study in quantifying the role of indirect network effects in the EV market and its implications on government subsidy policies (subsidizing the charging station investment versus subsidizing EV purchase). Similar to Li *et al.* [2017], Springel [2017] quantifies indirect network effects in Norway's EV market and also finds that subsidizing charging stations is more cost-effective than subsidizing EV purchase in the early stage of the EV diffusion process. Li [2016] focuses on the competing plug standards for charging stations and examines the impact of compatibility on investment in charging stations and consumer adoption.

While using similar data sets, the current study differs from Li *et al.* [2017] in three important aspects. First, the current study offers the first empirical analysis of the issues of multiple equilibria and critical mass in the EV market and their implications on regional-specific subsidy policies and long-run market outcomes. In contrast, Li *et al.* [2017] focus on the relative cost-effectiveness between subsidizing EV purchases and subsidizing charging station installation. Second, the empirical model in the current study is a parametric version of the theoretical model. It allows for multiple equilibria depending on the values of model parameters and market conditions, whereas Li *et al*. [2017] assume a unique equilibrium with positive adoption. Third, the price endogeneity is explicitly addressed in the current study and the identification relies on the firm-specific stringency of Corporate Average Fuel Economy (CAFE) Standards. Although existing literature has shown that in the short term, firms use the price strategy to help comply with CAFE, for example by reducing the price of fuel-efficiency vehicles per Klier and Linn [2012] and Jacobsen [2013], to our knowledge, our study is the first one to leverage the price variation induced by the CAFE compliance for identification in the demand estimation.

The remainder of this paper is organized as follows. Section II briefly describes the U.S. EV market. Section III presents a stylized model to show the technology diffusion and the critical mass phenomenon. Section IV presents the empirical strategy and estimation results. Section V characterizes the steady state and Section VI examines the policy impacts. Section VII concludes. All proofs are in the Appendix.

II. U.S. ELECTRIC VEHICLE MARKET

The U.S. transportation sector is a large source of harmful air pollutants and a significant contributor to U.S. dependency on foreign oil. According to the U.S. Environmental Protection Agency (EPA), the transportation sector accounts for about 20% of particulate matter (PM) emissions, nearly 30% of greenhouse gas emissions, over 50% of carbon monoxide and nitrogen oxides emissions, and about 25% of hydrocarbons emissions in recent years. The wide adoption of electric vehicles would fundamentally transform the way we power the transportation sector and could have important environmental and energy implications. Two types of EV's are currently on the market: battery electric vehicles (BEV's) that run exclusively on high-capacity batteries (e.g., Nissan LEAF), and plug-in hybrid electric vehicles (PHEV's) that use batteries to power an electric motor and use another fuel (gasoline) to power a combustion engine (e.g., Chevrolet Volt). When operated in all-electric mode, EV's consume no gasoline and produce zero tailpipe emissions.[3]

In March 2008, Tesla Motors began the general production of its all-electric sport car Tesla Roadster, leading the rollout of the new waves of electric vehicles.[4] The model had a price tag of over $120,000 and served a small niche market of very affluent buyers. In December 2010, Nissan introduced the Nissan Leaf (a BEV model) with a price of $28,980 and GM introduced

[3] Emissions shift from on-road vehicles to electricity generation. Therefore, the environmental benefit critically depends on the fuel source of electricity generation. If the electricity is generated from coal, EV's may have worse environmental performance than gasoline vehicles. In order to generate large environmental benefits, the diffusion of EV's needs to be coupled with cleaner electricity generation.

[4] From 1996 to 1998, GM introduced over 1000 first-generation EV's (EV1) in California, mostly made available through leases. In 2003, GM pulled out and destroyed their EV's upon the expiration of the leases.

Chevrolet Volt (a PHEV model) with a price of \$34,185, marking the beginning of the mass market for EV's. Monthly EV sales have increased from 345 in December 2010 to 24,785 in December 2016, with the number of EV models reaching 31 in 2016. Despite this rapid growth, the market share of electric cars is still small: total EV sales only made up 0.9% of the new light-vehicle sales in 2016.

Because of the potential of EV's to reduce air pollution and oil usage, many countries including the U.S. have set goals to develop the EV market and provide support in order to promote the diffusion of this technology.[5] The U.S. federal government has adopted several policies to support the EV market including providing federal income tax credits for EV purchase, R&D support for battery development, and funding for expanding charging infrastructure. The Congressional Budget Office [2012] estimates that the total budgetary cost for these policies will be about \$7.5 billion through 2017, and that the tax credits for EV buyers account for about one-fourth of the budget and have the largest aggregate impact on total EV sales among different types of policies. EV buyers in the U.S. are eligible for federal income tax credit ranging from \$2,500 to \$7,500, depending on the vehicle's battery capacity and the gross vehicle weight rating.[6] The credit will expire for the automaker once it has sold 200,000 qualified EV's. In addition to federal funding, several states have established monetary incentives such as sales tax exemptions and direct rebates for EV buyers and non-monetary incentives such as HOV lane access, toll reduction and free parking. For example, California's Clean Vehicle Rebate Project offers a \$2,500 rebate to BEV buyers and a \$1,500 rebate to PHEV buyers. Federal, state and local governments also provide funding to support charging station deployment. One important example is a \$115 million grant to build residential and public charging stations in 22 U.S. cities in collaboration with local partners, funded by the Department of Energy's EV Project and awarded to ECOtality, Inc.

During the launch stage of this new technology, government intervention could be warranted and prove crucial for the following three reasons. First, indirect network effects in the EV market represent a source of market failure since the marginal consumer or investor only considers the private benefit in their decision. As a result, the network size would be less than the socially optimal level. If all EV's are produced by one automaker, the automaker should have incentives to build a network of charging stations to

[5] In the 2011 State of the Union address, President Obama set up a goal of having one million EV's on the road by 2015 but the cumulative sales only reached 410,000 by the end of 2015. Similar national goals exist in many other countries. Chinese government set up a goal of half a million EV's on the road by 2015 and five million by 2020. German government developed an initiative to reach one million EV's by 2020.

[6] China's central government provides a rebate of over \$9,000 to BEV buyers and a rebate of nearly \$8,000 to PHEV buyers to offset the high price. The U.K. government offers a grant of up to \$7,800 to EV buyers. In Japan, EV buyers were eligible for a subsidy of up to \$10,000 in 2013 and \$8,500 in 2014.

increase EV adoption. In reality, all major automakers offer EV models, leading to the free rider problem in charging station investment. Second, as our model illustrates, a market may exhibit the critical-mass constraint under certain market conditions. In this case, government interventions can help the market overcome the critical mass hurdle and thus avoid the zero-adoption outcome in the steady state. Third, in the early stages of new technology diffusion, spillovers among firms often exist (Stoneman and Diederen 1994). The development of the EV technology requires significant costs but the technological knowhow, once developed, can spread through many channels, including worker migration and the product market.[7]

There are several factors that hinder the wide adoption of EV's as a new technology including high purchase cost, range anxiety due to limited driving range, lack of charging infrastructure, and long charging time. EV's are also much more expensive than their conventional gasoline vehicle counterparts. The 2014 Nissan Leaf and Chevrolet Volt have a manufacturer's suggested retail price (MSRP) of $28,980 and $34,185, respectively, while the price for a comparable gasoline vehicle (e.g., Chevrolet Cruze and Honda Civic) is between $16,000 and $18,000. The major reason behind the cost differential is the cost of the battery and as battery technology improves, the price differential is expected to drop over time.

BEV's have a shorter driving range per charge than that of conventional vehicles, contributing to consumer anxiety of running out of electricity before reaching a charging station. The Nissan LEAF, the most popular BEV in the U.S., has an EPA-rated range of 84 miles on a fully-charged battery in 2014 while the Chevrolet Volt has an all-electric range of 38 miles, beyond which it will operate in gasoline mode. This range is sufficient for most daily household vehicle trips but may not be enough for long-distance travels.

A wider distribution of publicly accessible charging infrastructure should mitigate range anxiety of BEV's and allow PHEV's to operate more in the all-electric mode to decrease the total gasoline consumption. The network of publicly accessible charging infrastructure is still inadequate: there are only around 11,000 publicly accessible EV charging stations by the end of December 2015 in the U.S., compared to more than 120,000 gasoline stations.[8]

In terms of charging time, it takes much longer to charge EV's than to fill up gasoline vehicles. EV's can be charged with a regular household electric plug (120 Volt) but a BEV may not be able to get fully charged overnight (it

[7] Bloom *et al.* [2013] estimate that the social returns to R&D are larger than the private returns due to positive technology spillovers, implying under-investment in R&D.

[8] Charging stations can be found at convenience stores, auto dealers, restaurants, shopping malls, workplace parking lots, as well as gasoline stations. They are often managed by one of the major national operators such as Blink, ChargePoint, and eVgo. Many charging stations are owned by non-profit entities and the service is often free as a benefit to customers or employees. Owners of charging stations are often motivated by considerations such as boosting their sustainability credentials and attracting customers for their main business.

takes 21 hours for the Nissan LEAF to get fully charged). Unlike BEV's, PHEV batteries can be charged not only by an outside electric power source, but also by the internal combustion engine while driving. Having the second source of power may alleviate range anxiety, but the shorter electric range limits their fuel cost savings. To get more convenient charging, EV drivers either need to install a charging station at home or go to public-accessible charging stations

There are two types of charging stations: Level 2 charging (240 volt AC charging) and DC fast charging (500 volt DC high-current charging), with the former being the dominant type. It takes 6-8 hours to fully charge a Nissan Leaf at a Level 2 charging station but only 10–30 minutes at a DC fast charging station. The installation of charging stations involves a variety of costs including hardware, other materials, labor and permits. A typical Level 2 charging station has 3–4 charging units and costs about $15,000, while a DC fast charging station costs over $50,000.

III. A THEORETICAL MODEL

In order to demonstrate the role of indirect network effects in the process of product diffusion and to identify market conditions when the critical-mass phenomenon is present, we begin with a stylized framework to characterize consumers' adoption decisions and investors' entry decisions in one geographic area. Our model is developed based on Gandal *et al.* [2000] who examine the indirect network effects between CD players and CD's and Greaker and Heggedal [2010] who examine the competition between traditional gasoline technology and hydrogen fuel technology by taking into account the network externalities. We extend their analysis by examining the property of steady-state equilibria and the critical mass issue in the process of reaching the steady-state equilibrium. Our goal is to analyze the role of policy interventions in promoting EV adoption in the presence of critical-mass constraints.

For simplicity, we assume that only one EV model exists and we shall show in Appendix A.1 that the framework can be modified slightly to accommodate the case of multiple EV models. At the beginning of time period t, Q_{t-1} consumers have already adopted EV's and $\bar{q}_t$ potential new consumers come to the market. Those new consumers decide whether to adopt an EV at time t. Meanwhile, an infinite number of private investors decide whether to build publicly-accessible charging stations. Consumers and investors make their decisions simultaneously. At the end of time period t, the installed base of EV's, Q_t and the number of charging stations, N_t are realized.

We take automakers' pricing and product choice decisions as given and focus on analyzing consumers' adoption behavior and investors' entry behavior. We show that multiple equilibria may exist in the presence of positive indirect network effects and that the critical mass phenomenon will emerge if the EV price is in a certain range. Given our analysis of consumers and investors' behavior, automakers or policy makers can implement appropriate strategies to help the market overcome the critical-mass hurdle and move to the high-adoption equilibrium. In our empirical analysis, we do not model automakers' or policy makers' decisions, and we use the instrumental variable technique to address the endogeneity in the key variables (such as the size of charging station network and vehicle prices) that arise from simultaneity or unobservables.

III(i). *EV Adoption*

The expected utility of consumer i from adopting an EV at time t is $\theta_i v(N_t^e) - \alpha_t P_t$. Here, N_t^e is the number of publicly-accessible EV charging stations that are expected by consumers at time t. θ_i captures consumer i's idiosyncratic preference for the public charging network, with a smooth cumulative density function $G_t(\cdot)$ on a non-negative interval $[0, \bar{\theta}_t]$, where the upper bound $\bar{\theta}_t$ may depend on local market conditions such as commute time to work and availability of residential charging facilities. $\theta_i v(N_t^e)$ captures consumer i's expected utility from the public charging network, with $v(\cdot)$ being non-negative and an increasing function. P_t is the EV price at time t which is known by consumers when they make their adoption decisions. α_t captures consumers' disutility from EV price that may depend on local demand conditions such as consumers' income, consumers' environmental awareness, and local gasoline prices.

If a consumer does not adopt any EV, we normalize her utility to be zero. Consumers are assumed to be myopic agents. The new sales of EV's at time t is a function of the expected number of charging stations:

$$q_t = \left[1 - G_t\left(\frac{\alpha_t P_t}{v(N_t^e)}\right)\right] \bar{q}_t. \tag{1}$$

Note that $q_t = 0$ if $N_t^e \leq \underline{N}_t \equiv v^{-1}(\alpha_t P_t / \bar{\theta}_t)$. That is, positive new sales require that N_t^e exceeds a threshold $\underline{N}_t$.

Let ρ denote the scrappage rate of EV's. Then, the installed base of EV's at time t is

$$Q_t = \left[1 - G_t\left(\frac{\alpha_t P_t}{v(N_t^e)}\right)\right] \bar{q}_t + (1-\rho) Q_{t-1}. \tag{2}$$

III(ii). *Supply of Charging Stations*

Within a time period t, denote each EV driver's demand for charging station k by $D_k(r_1, \cdots, r_N)$, where r_k is the rate charged by station k. We assume a constant marginal cost of charging station, denoted by c, which includes the electricity cost and the service cost. The per-consumer profit is $\pi_k = (r_k - c)D_k(r_1,\cdots,r_N)$. We assume that demand is symmetric and the profit function is quasi-concave in r_k. Given this assumption, there exists an equilibrium in which all stations charge the same rate and the equilibrium price would depend on the number of stations in the market, denoted as $r(N)$. Then the per-consumer profit for each station can be written as a function of the number of charging stations: $\pi(N) = (r(N)-c)D(r(N),\cdots,r(N))/N$. We assume that the equilibrium profit $\pi(N)$ is declining in the number of stations in the market, which is consistent with the properties of standard spatial competition models, including Salop's circle model and Cournot models.

Let Q_t^e denote the installed base of EV's at time t that is expected by investors and let C_t denote the building cost of a charging station at time t. If an investor builds a station at time t, its profit is $-C_t + Q_t^e \pi(N_t) + \delta Q_{t+1}^e \pi(N_{t+1}^e) + \cdots$, where δ is the investor's discount factor. If the investor who is assumed to have perfect foresight about the investment cost for the next period builds a station at time t+1, its discounted profit at time t is $-\delta C_{t+1} + \delta Q_{t+1}^e \pi(N_{t+1}^e) + \delta^2 Q_{t+2}^e \pi(N_{t+2}^e) + \cdots$. In a free-entry equilibrium, the investor should be indifferent between investment at time t and t+1. The number of charging stations can be written as a function of the installed base of EV's:

$$N_t = \pi^{-1}\left(\frac{C_t - \delta C_{t+1}}{Q_t^e}\right), \tag{3}$$

where $C_t - \delta C_{t+1}$ represents the relative cost of building a station today rather than tomorrow. Note that to achieve the minimal charging network for positive EV sales, $\underline{N}_t$, the expected installed base of EV's must be higher than $\underline{Q}_t = (C_t - \delta C_{t+1})/\pi(\underline{N}_t) = (C_t - \delta C_{t+1})/\pi(v^{-1}(\alpha_t P_t/\bar{\theta}_t))$.

III(iii). *Network Dynamics and Steady-State Equilibrium*

We focus on the equilibria with self-fulfilling expectations, $N_t = N_t^e$ and $Q_t = Q_t^e$. Substituting (3) into (1) gives the dynamic path of the EV installed base:

$$Q_t = \left[1 - G_t\left(\frac{\alpha_t P_t}{v\left(\pi^{-1}\left(\frac{C_t - \delta C_{t+1}}{Q_t}\right)\right)}\right)\right]\bar{q}_t + (1-\rho)Q_{t-1}. \tag{4}$$

From equation (4), we can write Q_t as a function of Q_{t-1}, denoted as $Q_t = \Psi_t(Q_{t-1})$. The shape of $\Psi_t(\cdot)$ depends on the shapes of $v(\cdot)$, $\pi(\cdot)$ and $G_t(\cdot)$, the EV price, the charging station installation cost, and the market size.

In the steady state, the network stays constant over time. That is, $Q_t = Q_{t-1}$ and $N_t = N_{t-1}$. We also assume $\bar{q}_t = \bar{q}$, $P_t = P$, $\bar{\theta}_t = \bar{\theta}$, $\alpha_t = \alpha$ and $C_t = C$ in the steady state. First of all, notice that there always exists a degenerated equilibrium where no consumer adopts EV and no investor builds charging stations. That is, $Q_t^* = 0$ and $N_t^* = 0$ for all t. This is the classical 'no-chicken-no-egg' outcome. Let Q^* and N^* respectively denote the installed base of EV's and charging stations in the steady-state equilibrium with positive EV adoptions. They are the solutions of the two cross-group response functions,

$$Q^*(N) = \left[1 - G\left(\frac{\alpha P}{v(N)}\right)\right] \bar{q}/\rho, \tag{5}$$

Here, equation (5) characterizes consumers' response to investors' supply of charging stations and equation (6) characterizes investors' response to consumers' adoption of EV's. Hence, the EV adoption at the steady-state equilibrium is given by

$$N^*(Q) = \pi^{-1}\left(\frac{(1-\delta)C}{Q}\right). \tag{6}$$

$$\rho Q^* = \left[1 - G\left(\frac{\alpha P}{v\left(\pi^{-1}\left(\frac{(1-\delta)C}{Q^*}\right)\right)}\right)\right]\bar{q}. \tag{7}$$

The steady-state equilibrium can fall short of full saturation depending on $\Psi(\cdot)$.[9] In other words, the model can accommodate failed adoption. The steady-state equilibrium is consistent with the static self-fulfilling expectation equilibrium in the literature (Katz and Shapiro 1985, 1986; Caillaud and Jullien 2003). Depending on the values of these parameters, in general we have three different structures of equilibrium outcomes.

Case I: No-Adoption Equilibrium

Figure 1(a) illustrates the first case in which $N^*(Q)$ and $Q^*(N)$ interact only at the origin. Hence the origin is the only equilibrium and it is globally stable. This case can arise either because the EV price is too high or because there are too few potential EV buyers with high values of θ_i and, as a result, the long-run equilibrium has no adoption no matter where the initial starting point is.

[9] Alternatively, we can plug equation (5) into (6) to get an equation that characterizes the dynamic process of charging station deployment and subsequently the critical-mass conditions. These two methods are theoretically equivalent. That is, if an MSA is found to suffer from the critical mass issue based on equation (7), the same result will also emerge based on the alternative characterization. For a given MSA, once we know its EV adoption level at the long-run equilibrium, we can always compute the number of charging stations in equilibrium from equation (6).

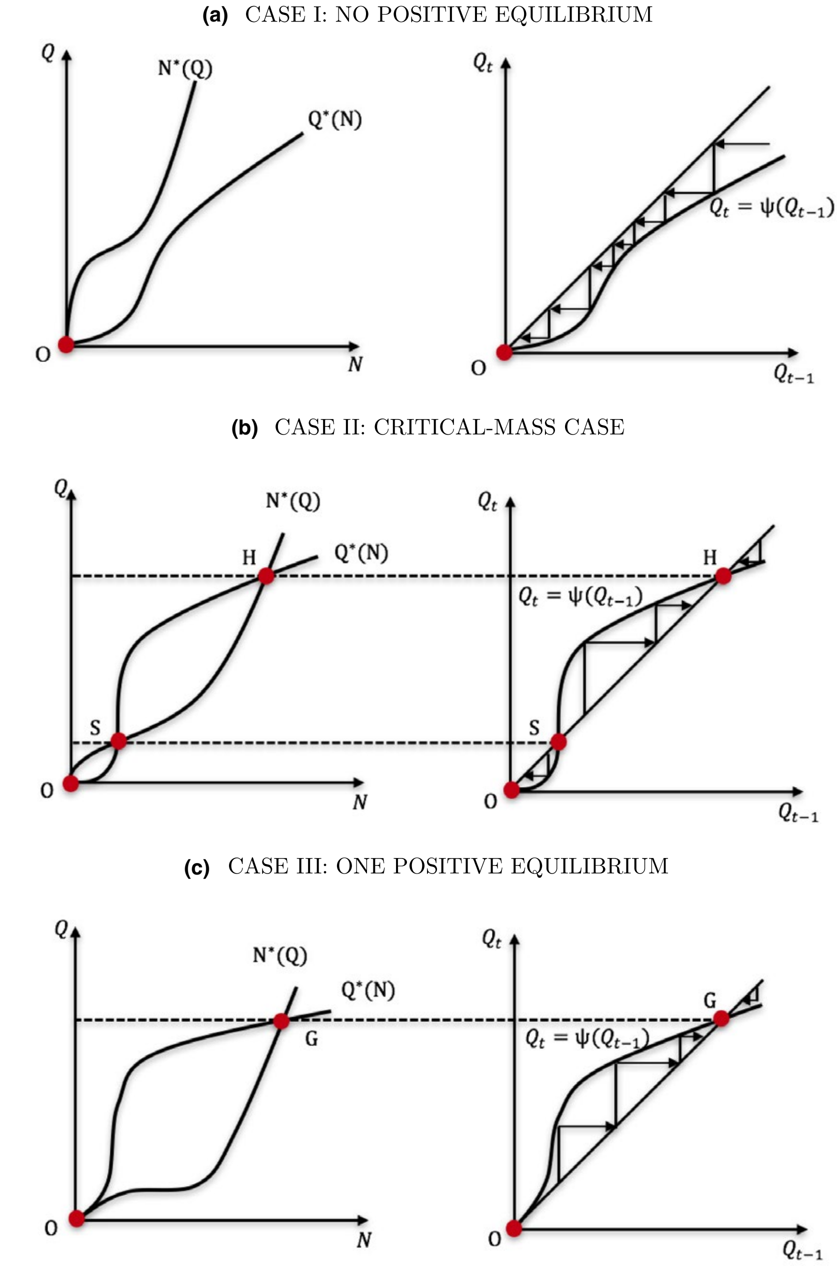

Figure 1
Three Types of Equilibrium Outcome

Notes: The left sub-figures present the two cross-group response curves, and the right sub-figures present the dynamic process of EV adoption

[Colour figure can be viewed at *wileyonlinelibrary.co*m]

Case II: Critical-Mass Case

Figure 1(b) illustrates the second case in which $N^*(Q)$ and $Q^*(N)$ interact at the origin O, and two points with positive EV adoption, denoted as points S and H. S is unstable (called critical mass) and H is locally stable.[10]

In general, there may be more than three equilibria. If so, theory (Burdett and Wright 1998) tells us that the locally stable equilibria and saddle-points must alternate. Trajectories beginning above the critical mass will converge to the high-adoption equilibrium H, while trajectories beginning below the critical mass will move back to the origin in the long run. In order for positive feedback loops to drive the market to point H rather than to the origin, the market needs to reach a point above the critical mass either by itself or through policy interventions. In this case, government policies can play an important role in helping the market overcome the critical mass hurdle and eventually reaching the high-adoption equilibrium.

Case III: One Positive Equilibrium

In Figure 1(c), $N^*(Q)$ and $Q^*(N)$ interact at the origin and point G with positive EV adoption, where the origin is an unstable equilibrium and G is a globally stable equilibrium. This scenario does not entail a critical mass, and a slight deviation from the origin is all that is necessary to set in motion the dynamic path toward the stable equilibrium G. This case can arise either because the EV price is very low or because there are many potential EV buyers with high values of θ_i. As a result, it is only a matter of time for the system to finally reach the high-adoption equilibrium G.

It is worth pointing out that in our model, consumers are assumed to be myopic decision makers. In reality, consumers may be forward-looking and they may choose one from all available vehicle models or delay their purchase decisions by taking into account their expectations of their choice set and vehicle attributes including vehicle price in future periods. Incorporating such dynamics in consumer adoption decisions can capture the fact that early adopters could be different from later adopters. However, analyzing a model with both dynamic EV adoption and dynamic station investment would require a lot of additional assumptions to maintain tractability both theoretically and computationally and necessitate more granular data over a sufficiently long period. We believe that this would be a promising direction for future research.

[10] When $N^*(Q)$ and $Q^*(N)$ are tangent at a point with positive EV adoption, S and H are the same. In this case, the equilibrium S (or H) is unstable, and the long-run market outcome is most likely zero adoption as in the first case.

III(iv). *Functional-Form Assumptions*

Equation (7) implies that the number and the magnitude of positive equilibria depend on the shapes of $v(\cdot)$, $G(\cdot)$, and $\pi(\cdot)$. To take the model to the data, we make the following functional form assumptions:

(i) $v(N_t) = (N_t)^{\tilde{\beta}_1}$ and $G_t(\theta) = \theta^{\tau}/\bar{\theta}_t^{\tau}$ on the interval $[0,\bar{\theta}_t]$. Here, the parameter $\tilde{\beta}_1$ measures consumers' reliance on the public charging network, and the upper bound $\bar{\theta}_t$ may depend on local market conditions such as commute time to work and availability of residential charging facilities.

(ii) $\pi(N_t) = \tilde{\eta}_t(N_t)^{\tilde{\gamma}_1}$, where $\tilde{\gamma}_1$ measures the extent of competition among charging stations and $\tilde{\eta}_t$ captures the impact of other factors that affect investors' benefit from building charging stations.

Under the assumptions above, equations (1) and (3) generate two log-linear equations that are convenient to work with empirically, one equation of EV demand and one equation of charging station investment:

$$ln(1-s_t) = \beta_1 ln(N_t) + \beta_2 ln(P_t) + \xi_t, \tag{8}$$

$$ln(N_t) = \gamma_1 ln(Q_t) + \gamma_2 ln(C_t - \delta C_{t+1}) + \eta_t, \tag{9}$$

where $s_t = q_t/\bar{q}_t$, $\xi_t = \beta_2 ln(\alpha_t) - \tau ln(\bar{\theta}_t)$, $\beta_1 = -\tau\tilde{\beta}_1$, $\beta_2 = \tau$, $\eta_t = -ln(\tilde{\eta}_t)/\tilde{\gamma}_1$, $\gamma_1 = -1/\tilde{\gamma}_1$, and $\gamma_2 = 1/\tilde{\gamma}_1$.

Here, ξ_t and η_t summarize other market conditions that affect consumers' demand for EV's and investors' supply of public charging stations. In markets with high household income, consumers tend to have a lower disutility from EV purchase, that is, a lower α. Given that β_2 is positive, equation (8) suggests that this market tends to have lower ξ and a higher demand for EV's.

β_1 and γ_1 capture the magnitude of the indirect network effects. Feedback loops arise if both β_1 and γ_1 are non-zero. Intuitively, a shock to the system (e.g., an increase in demand shifter at time t), would change EV sales q_t and therefore the installed base Q_{t+1}. This would then lead to changes in the number of charging stations N_{t+1} and hence affect q_{t+1}. The impact would circle back and forth between these two equations. If β_1 is negative and γ_1 is positive, positive feedback loops would arise and they can amplify either demand or supply shocks (either positive or negative) such as tax credits for EV purchases or subsidies for charging station investment. β_2 (positive) captures consumers' sensitivity to the EV price and γ_2 (negative) captures investors' sensitivity to the investment cost.

These two equations are similar to the equations characterizing the demand for CD's and the demand for CD players in Gandal *et al.* [2000]. As we discuss in the next section, an important difference is that our data includes the EV sales at the MSA-quarter-model level and number of charging stations at the MSA-quarter level, while their data contains total sales of CD players and sales of CD's over 30 quarters at the national level. Due to the richer nature of our data, we are able to control for the time-invariant product attributes, local demand shocks and time-varying national shocks. The inclusion of those fixed effects can help identify indirect network effects whereby instruments are constructed to address endogeneity due to simultaneity in EV demand and charging station supply.

III(v). *Long-Run Inverse Demand Curve*

The steady-state equilibria with positive EV adoptions are given by

$$(1-\rho Q^*/\bar{q})Q^{*-\beta_1\gamma_1} = P^{\beta_2}C^{\beta_1\gamma_2}(1-\delta)^{\beta_1\gamma_2+\beta_2}e^{\xi+\beta_1\eta}. \tag{10}$$

Suppose that the parameters have the expected signs: $\beta_1 < 0$, $\beta_2 > 0$, $\gamma_1 > 0$, $\gamma_2 < 0$.

Proposition 1. There exist two price cutoffs, P_{min} and P_{max}, such that:

Case I. When $P > P_{max}$, the origin is the only steady-state equilibrium and it is globally stable.

Case II. When $P_{min} < P \leq P_{max}$, the origin, S and H with $Q_H \geq Q_S > 0$ are the three steady-state equilibria. The origin and H are locally stable and S is unstable.[11]

Case III. When $P \leq P_{min}$, the origin and G with $Q_G > 0$ are the two steady-state equilibria. The origin is unstable and G is locally stable.

Proposition 1 implies that the critical mass phenomenon (Case II) exists if the EV price is between P_{min} and P_{max}. Plotting the EV adoption in the steady state under different EV prices provides the long-run inverse demand curve, see Figure 21. This inverted-U shape is consistent with the static fullfilled-expectations inverse demand curve in Economides [2007].

Furthermore, the long-run demand elasticity with respect to EV price is

$$\frac{\partial Q^*}{\partial P}\frac{P}{Q^*} = -\frac{\beta_2}{(1-\rho Q^*/\bar{q})^{-1}-1+\beta_1\gamma_1}.$$

Two implications are worth pointing out. First, consider the high-adoption equilibrium levels, Q_H in case (II) or Q_G in case (III). In the case of positive indirect network effects ($\beta_1 < 0$ and $\gamma_1 > 0$), the magnitude of the elasticity is larger than that in the case of no indirect network effects. This is because an increase in EV prices not only makes consumers less likely to purchase EV's, but also reduces their prediction of future EV stock and the size of the

[11] When $P = P_{max}$, S and H are the same. In this case, the equilibrium S (or H) is unstable.

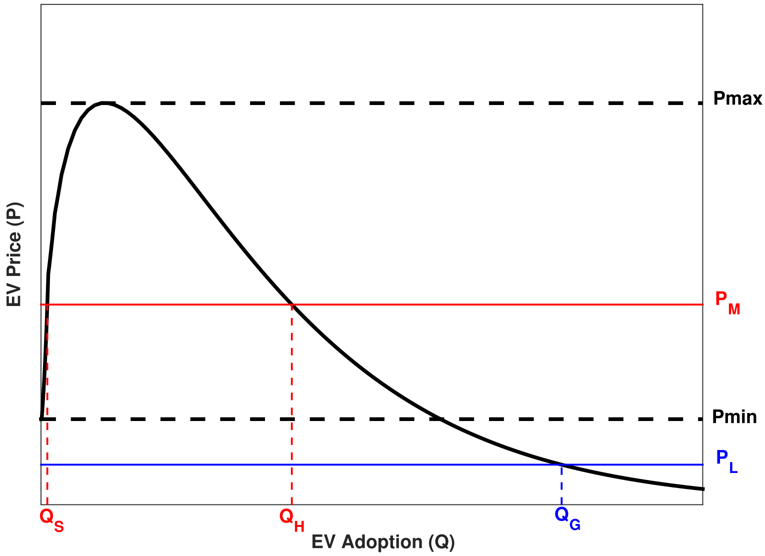

Figure 2
Inverse Demand Curve in the Steady State
[Colour figure can be viewed at *wileyonlinelibrary.com*]

charging station network, which further dampens their propensity for EV purchase. In other words, the impact of price on EV adoption in the steady-state equilibrium is amplified due to the positive indirect network effects and, moreover, the degree of amplification depends on the magnitude of the indirect network effects.

Second, in the critical mass case we have $\frac{\partial Q_S}{\partial P}\frac{P}{Q_S} > 0$ and $\frac{\partial Q_H}{\partial P}\frac{P}{Q_H} < 0$, that is, the critical mass level is increasing in EV price and the high-adoption equilibrium level is decreasing in EV price. Similarly, we can determine the dependence of Q_S (Q_H) on local market characteristics: market size ($\bar{q}$), consumers' preference for EV's (α), consumers' reliance on the public charging network ($\bar{\theta}$), and benefits from investing in charging stations (η).

Proposition 2. In the critical-mass case, the critical-mass level Q_S increases in P but decreases in $\bar{q}$, α, $\bar{\theta}$ and η, whereas the high-adoption-equilibrium level Q_H decreases in P but increases in $\bar{q}$, α, $\bar{\theta}$ and η.

In other words, the critical mass constraint is lower and the high-adoption-equilibrium level is higher for markets with lower EV price, larger market size, stronger preference for EV's, stronger reliance on the public charging network, and higher benefits from investing in public charging stations. For example, a richer household is less sensitive to EV price, that is, having a lower α. Proposition 2 suggests that the critical mass constraint (Q_S) is lower and the high-adoption level (Q_H) is larger for markets with high household income.

III(vi). *Policy Implications*

There exist many policies at the federal, state and local levels to promote the adoption of EV's with the most prominent being the federal subsidies for EV buyers. Our analysis implies that the policy impact depends on the magnitude of indirect network effects. The stronger the feedback loops, the larger the impact of the subsidy policies on EV adoption.

From Figure 2, we can qualitatively see how a price reduction affects the EV adoption in the steady state. For a market in which the EV price is below the lower threshold P_{min} (case III), and hence only a slight positive shock can automatically drive this market to the high-adoption equilibrium G, lowering the EV price would increase the level of high-adoption equilibrium Q_G. For a market in which the EV price is above the upper threshold P_{max} (case I) or between the two price thresholds (case II), so that it does not have any positive adoption in the steady state, a sufficient reduction of the EV price would convert this market to Case III and lead to a positive EV adoption in the steady state.

However, the quantitative impact of a particular subsidy policy depends on the location of the long-run demand curve, especially the two price thresholds, P_{min} and P_{max}. In the following sections of the paper, we shall estimate the model using panel data of quarterly EV sales and charging stations across 354 MSA's over twelve quarters, use the estimated parameters to simulate the steady-state equilibrium EV adoption for each of the MSA's, and quantify the impacts of the current federal subsidy policy and alternative subsidy policies.

IV. EMPIRICAL ANALYSIS

In this section, we first present the data used in the empirical analysis, then we present our estimation strategy and report the results.

IV(i). *Data*

Our data includes quarterly EV sales by vehicle model and the number of charging stations in each of the 354 MSA's from 2011 to 2013. The sales data in each MSA is obtained from IHS Automotive and it includes 17 EV models in 2013: 10 BEV's and 7 PHEV's. The top four EV models are Nissan Leaf, Chevrolet Volt, Tesla Model S and Toyota Prius plug-in with market shares (sales) in the EV segment being 25.8% (22,610), 24.4%

(23,094), 17.4% (18,650) and 9.4% (12,088) in 2013, respectively. The total EV sales of those 354 MSA's accounted for 83% of national EV sales during our data period.

The detailed information on locations and open dates of all charging stations comes from the Alternative Fuel Data Center (AFDC) of the Department of Energy. Based on the open date and the Zip code information of stations included in the AFDC data as of January, 2014, we construct the total number of available stations by MSA and by quarter. Modifications to a station such as adding charging outlets do not constitute a new station. Moreover, we assume that there was no exit during our sample period from 2011 to 2013. To examine this assumption, we compared the AFDC data recorded in January, 2013, with the one recorded in January, 2014. We did not find any exits, i.e., stations that were included in the 2013 data but not the 2014 data. We consider this as evidence that exit is rare if at all during our sample period.

We also collect information on the number of residential charging facilities built from the EV Project, a DOE-sponsored charging infrastructure program, in each of the 22 participating MSA's. The installation costs in our analysis are the national average costs minus the federal and local subsidies. Specifically, a typical Level 2 charging station with 3-4 charging units costs about $27,000 while a DC fast charging station costs $50,000.[12]

Figure B.1 in the web appendix depicts the spatial distributions of EV's and charging stations at the end of 2013. The MSA with the highest concentration is San Jose-Sunnyvale-Santa Clara, California, with 5,608 EV's per million people by the end of 2013. The next two MSA's are both nearby: San Francisco-Oakland-Fremont and Santa Cruz-Watsonville. The MSA with the lowest concentration is Laredo, Texas, with only 36 EV's per million people (9 EV's with a population of a quarter of a million). The top three MSA's with the most charging stations per million people are Corvallis, Oregon, Olympia, Virginia, and Napa, California, with 210, 170 and 117 public charging stations per million people, respectively. These three MSA's are 11th, 5th, and 6th in terms of the EV concentration. The correlation coefficient between the number of EV's and the number of charging stations per million people is 0.63, partly reflecting the interdependence of EV's and charging stations.

For auxiliary data, we collect information from the AFDC on state-level incentives such as tax credits and rebates for both electric vehicles

[12] According to the charging station cost report by the U.S. Department of Energy Vehicle Technologies Office [2015], the cost of a level-2 EV charging unit for public use is between $3,000 and $6,000, and the installation fee is from $600 to $12,700 per unit. Using the average equipment cost ($ 4,500) and installation fee ($3,000) per unit, the total cost of installing a charging station of an average size (3.6 charging units) comes to $27,000. This estimate does not include future maintenance and operating costs and is therefore a lower bound estimate. An upper bound estimate which includes those costs can be found at *http://www.afdc.energy.gov/uploads/publication/evse_cost_report_2015.pdf*.

and charging stations. From the American Chamber of Commerce cost-of-living index database, we collect quarterly gasoline prices for each MSA from 2008 to 2013. In the case of missing MSA's in the cost-of-living data, we use the average price of other cities in the same state. We also collect household demographics such as household income and average commute time to work from the American Community Survey.

Table I provides summary statistics of variables for the EV demand equation and the charging station supply equation in our empirical analysis. There are significant variations in EV sales and charging station networks across MSA's. The EV adoption and the station deployment grew rapidly from 2011 to 2013, along with an increase in the average EV price (due to the entry of more expensive models) and an increase in the average household income during this period.

IV(ii). *Empirical Framework*

Let j denote an EV model such as the Nissan Leaf or the Tesla Model S, m denote an MSA, and t denote a year-quarter such as the first quarter of 2011. We estimate the empirical counterparts of the EV demand equation (8) and the charging station supply equation (9):

$$ln(1-s_{jmt}) = \beta_1 ln(N_{mt}) + \beta_2 ln(p_{jmt}) + \beta_3' X_{jmt} + \vartheta_{jmt}, \tag{11}$$

$$ln(N_{mt}) = \gamma_1 ln(Q_{mt}) + \gamma_2 ln(C_{mt} - \delta C_{mt+1}) + \gamma_3' Z_{mt} + \omega_{mt}. \tag{12}$$

In equation (11), $s_{jmt} = q_{jmt}/\bar{q}_{mt}$, the market share of EV model j in MSA m at time t is defined as the sales of model j in MSA m at time t divided by the number of potential vehicle buyers. Following the theoretical model, the dependent variable in this equation is the market share of non-EV's and the coefficient estimates can be interpreted as the impact on non-EV demand. The unit of observation is MSA-quarter-model across 354 MSA's and 12 quarters for 17 EV models from 2011 to 2013. N_{mt} is the total number of charging stations that have been built in MSA m by the end of the year-quarter t. p_{jmt} is the effective price, defined as the manufacturer's suggested retailer price (MSRP) less the related subsidies (tax credits and tax rebates at both federal and state levels). X_{jmt} is a vector of other control variables including local gasoline price, HOV exemption for EV's, home charging subsidy[13], average annual household income, and a full set of MSA-vehicle model fixed effects (e.g., Nissan Leaf in San Francisco) and year-quarter fixed effects (e.g., the first quarter of 2011).

[13] EV's can be charged through a regular household power outlet but it is very slow. Some states provide home charging subsidies for EV buyers to install Level 2 charging at home (240 volt AC charging). The number of Level 2 charging stations at private homes may not have a direct impact on future EV adoption as public-accessible charging stations do.

TABLE I
SUMMARY STATISTICS

Variables	2011		2012		2013	
	Mean	Std.dev	Mean	Std.dev	Mean	Std.dev
EV Demand Equation						
Market share of EV models	0.001	(0.003)	0.005	(0.007)	0.015	(0.029)
No. of charging stations	7	(14)	19	(37)	26	(51)
EV price ($)	29,122	(4,072)	32,316	(18,537)	33,731	(20,700)
Gasoline price ($)	3.563	(0.260)	3.562	(0.267)	3.496	(0.245)
EV project	9	(58)	19	(103)	20	(107)
HOV exemption for EV's	0.377	(0.485)	0.330	(0.470)	0.336	(0.472)
Annual household income ($)	39,717	(7,474)	41,465	(8,114)	42,051	(8,299)
No. of grocery stores	295	(653)	286	(632)	275	(621)
CAFE standard	27.5	(0.755)	27.8	(1.255)	30.381	(1.303)
Actual fuel efficiency	23.286	(0.748)	24.599	(0.939)	24.923	(1.290)
Commute time to work (min)	23.197	(3.416)	22.985	(3.341)	22.925	(3.344)
Number of observations		1,189		3,804		8,573
Charging Station Supply Equation						
No. of charging stations	3	(9)	11	(27)	15	(37)
EV installed base	17	(79)	81	(272)	257	(803)
Building cost ($)	15,128	(2,323)	15,115	(2,327)	15,115	(2,327)
Northeast network	0.034	(0.181)	0.136	(0.342)	0.136	(0.343)
Public funding or grants	0.267	(0.443)	0.355	(0.479)	0.344	(0.475)
Current gasoline price ($)	3.491	(0.307)	3.527	(0.268)	3.454	(0.255)
Gasoline price last year ($)	2.747	(0.150)	3.491	(0.307)	3.527	(0.268)
Gasoline price two years ago ($)	2.096	(0.136)	2.747	(0.150)	3.491	(0.307)
Number of observations		1,416		1,416		1,062

Notes: The unit of observation is MSA-quarter-model for the EV demand equation and MSA-quarter for the charging station supply equation. The variables are not scaled by the population or geographic size of the MSA. The market share of an EV model in an MSA is defined as the sales in the MSA over the number of potential vehicle buyers, $s_{jmt} = q_{jmt}/\bar{q}_{mt}$. From the American Community Survey, we obtain the total number of households in each MSA. We use the inter-purchase time for new cars (7 years or 28 quarters, see Albuquerque and Bronnenberg 2012) to account for the fact that consumers who have purchased a new car recently will not look for a new car and will not be part of the potential market. The total potential buyers in an MSA m in quarter t is given by $\bar{q}_{mt} = \#households_{mt}/interpurchase\ time$.

In this regression, MSA-vehicle model fixed effects not only control for time-invariant product attributes such as quality and brand loyalty that could affect vehicle demand but also control for time-invariant local preference for green products (Kahn [2007]) and demand shocks for each model (e.g., a stronger preference or dealer presence for the Nissan Leaf in San

Francisco). ϑ_{jmt} is the unobserved demand shocks at the MSA-vehicle model-year quarter level, including consumers' MSA-specific and time-varying idiosyncratic tastes for a specific EV model and local government's time-varying subsidy for purchasing a specific EV model.

One concern for the demand estimation is the supply shortage and limited availability of EV models during the sample period. The estimates would be biased if the supply constraints vary across MSA's and quarters and also correlate with our key regressors such as the charging station network. However, auto dealers often trade with other dealers to address shortages.[14] Because of this dealer-to-dealer trading, the dealer or MSA- level shortage would spread out across dealers and MSA's especially on a quarterly basis. In other words, the MSA-specific supply shortage would iron out over a longer period (e.g., a quarter) such that the supply shocks can be viewed as national-level shocks and hence captured by year-quarter fixed effects.

In equation (12), Q_{mt} denotes the installed base of EV's in MSA m at time t. C_{mt} is the building cost of a charging station including installation and equipment after federal and local tax credits. Z_{mt} is a vector of other covariates affecting investors' investment decisions including an indicator variable indicating whether MSA m belongs to the Northeast Electric Vehicle Network (NEVN) at time t,[15] an indicator variable indicating whether there exist public grants or funding to build charging infrastructure, and a full set of MSA fixed effects and year-quarter fixed effects. The MSA fixed effects control for time-invariant and MSA-specific preferences for charging stations. For example, some MSA's may be 'greener' than others and invest more on alternative fuel infrastructure. Similarly, MSA's with a higher population density and limited private installment of publicly-accessible charging stations may have more charging stations. The year-quarter fixed effects control for time-varying common shocks to charging station investment across MSA's such as macro-economic conditions. The error term ω_{mt} captures the unobserved time-varying local shocks to charging station investment, for instance, the unobserved time-varying local policies to support charging station installation.

In Section III we showed that the system of EV adoption and station supply may exhibit multiple equilibria depending on the values of the model parameters and market conditions. Consequently, the equilibrium EV adoption level may not be a unique function of structural parameters. Following the same logic as in Aguirregabiria and Mira [2007], we estimate

[14] For example, *https://www.autotrader.com/car-tips/buying-a-car-can-dealerships-trade-cars-227858*.

[15] NEVN was launched in late 2011 after a near one-million-dollar grant was announced in September 2011 by the Department of Energy. It is one of the Transportation and Climate Initiative of the mid-Atlantic and Northeast States (TCI) projects to facilitate planning for the deployment of electric vehicle charging stations and related infrastructure throughout the region and work together to attract additional public and private investment in infrastructure for clean vehicles. Participating in NEVN would lower the cost of installing public charging stations.

the two cross-group response functions that are unique functions of structural parameters and the choice of the other group. To deal with the endogeneity and simultaneous issues, we will use the instrumental variable method and describe it in detail in the following sections.

IV(iii). *EV Demand Equation*

There are two identification challenges in Equation (11). First, EV demand and charging station supply are determined simultaneously, and hence the charging station variable N_{mt} is endogenous. Second, EV prices could be correlated with unobserved product attributes via automakers' price setting decisions. In addition, we do not observe retail prices of EV's and instead use MSRP's to construct consumer prices, leading to measurement error and potential attenuation bias. Failing to control for the price endogeneity could lead to downward bias in price coefficient estimates (Berry *et al.* [1995]; Beresteanu and Li [2011]). We address these challenges with instrumental variables.

(*A*). *Instrumental variables for charging station network and EV price*

Following Li *et al.* [2017], we instrument for the charging station network size $ln(N_{mt})$ using the interaction between the number of grocery stores and supermarkets in an MSA at the end of 2012 with the number of the charging stations in all MSA's (lagged for one quarter).[16] As we discussed in Section II, many charging stations are owned by grocery stores and supermarkets who build them to attract customers and boost green credentials, among other reasons. The parking lots of grocery stores and supermarkets could be good sites for charging stations because EV drivers can charge their vehicles while shopping in the stores.[17]

Because the number of grocery stores does not vary with time in our sample period, it would be absorbed by the MSA fixed effects. To introduce temporal variation, we multiply it with the lagged number of charging stations in all MSA's. The aggregate number of charging stations in all MSA's captures the national-level trend in charging station investments due to aggregate shocks such as temporal variations in costs, investor confidence and federal incentive programs. The construction of this IV is similar in spirit to the Bartik instrument used in the labor literature to isolate local labor demand changes (Bartik [1991]). The intuition behind the IV strategy

[16] In a robustness check, we use the number of charging stations in all the other MSA's (lagged for one quarter) to address the potential endogeneity concern. The results are nearly identical.

[17] Nissan has been actively partnering with grocery stores to build charging stations. Kroger, the country's largest grocery store owner, has installed about 300 charging stations across the country.

is that national shocks to charging station investment could have differential impacts on charging station investment across MSA's: the MSA's with a larger number of grocery stores and supermarkets (hence better endowment of good sites for charging stations) will be affected by national shocks more than others. Our first-stage results in Table II show that the interaction term has a positive and highly statistically significant impact on charging station investments.

A potential threat to the exogeneity assumption is that different MSA's may have different susceptibility to national-level demand shocks and the number of grocery stores could be correlated with this susceptibility for some reason. In our model, however, the MSA fixed effects should capture those time-invariant unobservables and the year-quarter fixed effect should control for those time-varying shocks that are common across MSA's. Nevertheless, as a robustness check, we include a variety of MSA-level controls interacting with the time trend to control for potential heterogeneity in the diffusion path of EV's across MSA's, and our results show that our baseline results are robust to the inclusion of those interactions, providing further support for the exogeneity of the IV.

In order to identify the price coefficient β_2, we construct an IV from automakers' price setting conditions. The literature on automobile demand (Bresnahan [1987] and Berry *et al.* [1995]) typically assumes that

TABLE II

FIRST-STAGE REGRESSIONS OF THE EV DEMAND EQUATION

	(I): $ln(N_{mt})$		(II): $ln(p_{jmt})$	
ln(grocery stores$_m$)*ln(stations$_{t-1}$)	0.168***	(0.019)	0.000	(0.001)
$CAFE_{ft-1} - \overline{MPG}_{ft-1}$	−0.003	(0.006)	−0.080***	(0.002)
ln(gasoline price)*BEV	0.056	(0.118)	0.104***	(0.012)
ln(gasoline price)*PHEV	0.122	(0.115)	−0.060***	(0.009)
ln (residential charging from EV project)	−0.010	(0.034)	0.004	(0.001)
HOV exemption for EV's	−0.055	(0.072)	0.002	(0.002)
ln(household income)	-0.160	(0.927)	0.010	(0.078)
Model-MSA FE	Y		Y	
Year-Quarter FE	Y		Y	
R^2	0.671		0.530	
Joint F-statistic of IVs	57.36		291.23	
Observations	13,501		13,501	

Notes: ln(grocery stores$_m$)* ln(stations$_{t-1}$) is the interaction between the number of grocery stores at the end of 2012 and the total number of charging stations in last quarter across all MSA's. $CAFE_{ft-1} - \overline{MPG}_{ft-1}$ is the difference between an automaker's CAFE target and its actual fuel economy last year. Clustered standard errors at the MSA level are in parentheses.

*p<0.10, **p<0.05, ***p<0.01.

automakers engage in Bertrand (price) competition to maximize their own profits. Price markups (above marginal costs) are affected by own- and cross-price elasticities of demand as well as the regulatory constraints such as the Corporate Average Fuel Economy (CAFE) standards.

From 2011, the CAFE standards are reformulated to footprint-based standards. Each automaker needs to meet a firm-specific target based on its own fleet. The target is production-weighted harmonic mean fuel economy, expressed in miles per gallon, of an automaker's fleet of current model year passenger cars or light trucks produced for sale in the United States. Formally, an automaker's CAFE target for passenger vehicles in year t is $CAFE_{ft} = \frac{\sum_{j \in J_{ft}} q_j}{\sum_{j \in J_{ft}} q_j / \bar{e}_j}$, where q_j is the sales of model-year j, J_{ft} is the set of automaker's model-year passenger vehicles in year t, and $\bar{e}_j$ is the fuel economy requirement of model-year j which is determined by its footprint.

Automakers are allowed to accumulate credits when their fuel economy is higher than their targets and to use these credits in the next three years. They are also allowed to borrow against future credits as long as they repay the debt within three years. However, if an automaker fails to repay its debt within three years, it will be found in violation of the regulation and assessed a fine for each mile per gallon it falls below its targeted fuel economy multiplied by the total number of vehicles in the fleet. The fine has been increasing over years. This banking and borrowing scheme generates variations in the stringency of the standard over time.

As the CAFE standards become more stringent over time, automakers may reduce the price of fuel-efficient models and increase the price of fuel-inefficient models as a short-term compliance strategy and adjust their fleet composition through redesigning and introducing new fuel-efficient models in the medium and long terms (see Klier and Linn [2012]; Jacobsen [2013]; and Roth [2015]). CAFE standards present varying compliance challenges across automakers due to differences in fleet composition. We expect that the CAFE stringency may affect vehicle prices and we use a measure of firm-level CAFE stringency as an IV for EV prices.[18]

Let e_j denote the actual fuel economy of car-model j. Then automaker f's actual fuel economy is $\overline{MPG_{ft}} = \frac{\sum_{j \in J_{ft}} q_j}{\sum_{j \in J_{ft}} q_j / e_j}$.[19] We use the difference between an automaker's CAFE target in year $t-1$ and its actual fuel economy in year

[18] Even if a manufacturer always pays the fine due to noncompliance such as European automakers, the manufacturer may still take vehicle fuel economy into price-setting decisions because the total fine is proportional to the gap between the realized fuel economy and the firm-specific target.

[19] To encourage early adoption and the introduction of alternative fuel vehicles (AFV's) such as EV's, incentives are provided in CAFE compliance. In calculating the actual fuel economy for compliance, the fuel economy of EV's is computed as the average of its electric rating—divided by 0.15 (equal to multiplying by 6.666) – and its gasoline rating. The fuel economy for the plug-in Toyota Prius is 69.8 (MPG equivalent) and 141.7 for the Nissan LEAF relative to their 2016 target fuel economy of 34.0 MPG (44 sq. ft. footprint).

$t-1$ as an instrument for its EV prices in year t. Automakers who had a tougher time to meet CAFE standards in the previous year may have incentives to price EV's more aggressively to increase sales, which could in turn help CAFE compliance. Our first-stage results in Table II show that this difference has a negative and highly significant impact on EV prices, consistent with the short-term pricing strategy to comply with CAFE standards.

One concern on the exogeneity assumption of the CAFE instrument is that policy makers may modify the CAFE standards in response to the unobserved EV demand shocks. The footprint-based standard for cars of model year 2011–2015 was proposed by the Obama administration in 2009, before the introduction of EV's. Even if the standard set in 2009 had incorporated the emerging fuel economy technologies such as EV's, this type of correlation would likely have been at the national level and could be controlled by the time (year-quarter) fixed effects. In other words, model-specific demand shocks are unlikely to be correlated with the rule of the standard (i.e., the targets as a function of vehicle footprint) which applies to all vehicle models.

(*B*). *Baseline estimation results*

Table III reports the estimation results of the EV adoption equation. The first column reports the OLS estimation results and the remaining columns report the 2SLS estimation results. The second column (2) only instruments for $ln(N_{mt})$ using the interaction between the number of grocery stores in an MSA at the end of 2012 and the total number of stations in all MSA's in the previous quarter. The third column only instruments for $ln(p_{jmt})$ using the difference between an automaker's CAFE standard and its actual fuel economy last year. The last column instruments for both $ln(N_{mt})$ and $ln(p_{jmt})$.

All regressions provide negative and statistically significant impacts of the availability of charging stations on non-EV demand, ranging from -0.005 to -0.012. This implies that a larger charging station network would increase the demand for EV's, suggesting a positive indirect network effect. Interestingly, after instrumenting for $ln(N_{mt})$, the estimates of its coefficient become larger in magnitude, implying that OLS underestimates consumers' valuation of charging infrastructure in making EV adoption decisions. This could be due to unobserved demand shocks that are negatively correlated with the size of the charging station network. One example of such unobservables are the home charging incentives from local electric utilities. As a demand-side management program, some local utilities provide their customers subsidies for installing a home charging station and discounts in electricity price for home EV charging during non-peak hours. Local

TABLE III
EQUATION ON EV DEMAND

	(1)	(2)	(3)	(4)
	OLS	IV	IV	IV
ln(No. of stations)	-0.006^{***}	-0.012^{***}	-0.005^{***}	-0.012^{***}
	(0.001)	(0.004)	(0.001)	(0.005)
ln(EV price)	0.026^{***}	0.026^{***}	0.050^{***}	0.051^{***}
	(0.007)	(0.007)	(0.011)	(0.012)
ln(gasoline price)*BEV	-0.021^{***}	-0.021^{***}	-0.026^{***}	-0.025^{***}
	(0.008)	(0.007)	(0.008)	(0.008)
ln(gasoline price)*PHEV	-0.014^{*}	-0.013^{*}	−0.011	−0.011
	(0.008)	(0.008)	(0.008)	(0.008)
ln (EV project)	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
HOV exemption for EV's	-0.003^{**}	-0.003^{*}	-0.003^{**}	-0.003^{*}
	(0.001)	(0.002)	(0.001)	(0.002)
ln(household income)	-0.273^{**}	-0.278^{**}	-0.271^{**}	-0.275^{**}
	(0.125)	(0.124)	(0.125)	(0.124)
IV for ln(No. of stations)	N	Y	N	Y
IV for ln(EV price)	N	N	Y	Y
Model-MSA FE	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y
Observations	13,538	13,249	13,285	13,249

Notes: The dependent variable is $ln(1-s_{jmt})$, the market share of non-EV's following the theoretical model. The IV for log (No. of charging stations) is the interaction between log(number of grocery stores at the end of 2012) and log(total number of charging stations in last quarter across all MSA's), and the IV for EV price is the difference between an automaker's CAFE target and its actual fuel economy last year. Residential charging from EV project is the number of residential charging stations built through the DOE-sponsored EV project in each of 22 participating MSA's. Clustered standard errors at the MSA level are in parentheses.

$^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

government agencies often partner with local utilities to provide more generous home charging incentives when there is a lack of private investment in publicly-accessible charging stations.

The coefficients on the EV purchase price (MSRP's minus subsidies) are positive across all columns and statistically significant, implying a negative price effect on EV adoption. The price effect becomes stronger after correcting for price endogeneity, suggesting that local prices are positively correlated with unobserved time-varying local demand conditions (e.g., local governments provide stronger incentives when facing negative demand shocks on EV's). The direction of bias is also consistent with attenuation bias due to classical measurement error in the price variable due to the lack of retail prices.

To get a sense of the economic magnitude of the coefficient estimates, it is useful to consider how large of a price reduction is needed to compensate for one fewer charging station. Based on the estimates of our preferred specification (column 4), when the number of charging stations decreases by one, the equivalent price reduction is \$355 on average.[20] At the sample maximum of 320 charging stations, one fewer charging station is only equivalent to a price reduction of \$24 in EV demand, showing the diminishing effect implied by the log-log functional form.

The negative sign of the gasoline price coefficients implies that people are more likely to adopt EV's if the gasoline price is higher. The coefficient estimates are statistically significant for BEV models but not significant for PHEV models. BEV's run on electricity only while PHEV's can run both on electricity and gasoline. In reality, due to the limited drive range of the current PHEV models, PHEV drivers still need to use gasoline for most long-distance travels. Hence, the fuel savings of BEV models, compared to traditional gasoline vehicles, relies more on the gasoline price than it does for PHEV models. The residential charging facilities from the DOE-sponsored EV project have a positive but insignificant impact on EV adoption, and HOV exemption for EV's also spurs EV adoption. The coefficients before the household income are negative and statistically significant, implying that high-income consumers are more likely to adopt EV's than low-income consumers, which is consistent with the results of the California Plug-in Electric Vehicle Owner Surveys.[21]

(*C*). *Alternative specifications*

We take the estimates in column (4) of Table III as our baseline specification for the EV demand equation. To check the robustness of our baseline results, we estimate a variety of alternative specifications that either exclude some specific EV models or states from our sample, add more control variables, add additional instrumental variables, or use different demand specifications.

Sample Selection

Tesla vehicles are significantly more expensive than other EV modelss and they serve a different niche market with very affluent consumers. Therefore,

[20] The sample mean of EV price is \$32,930 and the sample mean number of charging stations is 22.229. Let x denote the price reduction that is needed to compensate for one fewer charging station. By definition, $-0.012\times[ln(22.229)-ln(21.229)]+0.051\times[ln(32930)-ln(32930-x)]=0$, so $x=\$155$.

[21] The percentages of the EV owners' household income being above \$150,000 are 54%, 47% and 50% for the 2012 survey, 2013 survey and 2014 survey, respectively.

TABLE IV
ROBUSTNESS CHECKS FOR EV DEMAND

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(No. of charging stations)	−0.012**	−0.011**	−0.006***	−0.011***	0.142***	−0.009***	−0.009***
	(0.005)	(0.004)	(0.002)	(0.004)	(0.049)	(0.004)	(0.004)
ln(No. of stations)*BEV				−0.002			
				(0.003)			
ln(No. of stations) * ln(commute time)					−0.045***		
					(0.015)		
ln(EV price)	0.052***	0.038***	0.060***	0.046***	0.050***	0.048***	0.048***
	(0.012)	(0.010)	(0.015)	(0.008)	(0.011)	(0.011)	(0.011)
ln(gasoline price)*BEV	−0.034***	−0.014***	−0.017***	−0.024***	−0.024***	−0.025***	−0.025***
	(0.009)	(0.007)	(0.004)	(0.008)	(0.008)	(0.008)	(0.008)
ln(gasoline price)*PHEV	−0.009	−0.003	0.003	−0.011	−0.009	−0.011	−0.011
	(0.008)	(0.008)	(0.005)	(0.008)	(0.008)	(0.008)	(0.008)
ln (EV project)	−0.001	−0.001	0.001	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HOV exemption for EV	−0.003**	−0.002	−0.002***	−0.003*	−0.002***	−0.003**	−0.003**
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
ln(household income)	−0.275**	−0.045*	−0.103**	−0.273**	−0.269**	−0.274**	−0.274**
	(0.124)	(0.025)	(0.049)	(0.123)	(0.124)	(0.124)	(0.124)
College share*time trend			−0.052***				
			(0.013)				
White share*time trend			−0.015*				
			(0.008)				

Asian share*time trend			-0.245^{***}				
			(0.059)				
Drive-to-work share			−0.039				
*time trend			(0.030)				
Model-MSA FE	Y	Y	Y	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y	Y	Y	Y
Over identification test						0.0003	0.0040
Under identification test						0.0000	0.0000
Observations	12,288	11,806	10,663	13,249	13,285	13,249	13,249

Notes: The dependent variable is $ln(1-s_{jmt})$, the market share of non-EV's. The IV for EV price is the difference between an automaker's CAFE target and its actual fuel economy last year. Column (1) excludes Tesla models from the analysis while Column (2) excludes California. Columns (1)–(5) instrument for log (No. of charging stations) with the interaction between log(no. of grocery stores) and log(no. of charging stations in last quarter in all MSA's). Column (6) adds a participation dummy variable for participation in the Northeast Network as an additional IV, and column (7) adds two other IVs, tax credit for charging stations and public funding for charging stations. Clustered standard errors at the MSA level are in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Tesla buyers may be quite different from other EV buyers (Sexton and Sexton [2014]). To check the robustness of our results, we exclude all Tesla models from our sample and report the estimation results in column (1) of Table IV. California has implemented the Zero-Emission Vehicle (ZEV) mandates that require a growing percentage of new vehicle sales by an automaker to be ZEV's (EV's and hydrogen vehicles). Thus, consumers and investors in California may behave differently from those in other states. We estimate our demand equation by excluding all California MSA's and report the results in column (2) of Table IV. Overall, our baseline results are robust to excluding Tesla models or California.

Additional Control Variables and Alternative IV's

We first add more control variables to our baseline specification and report our results in Table IV. To further control for MSA-level heterogeneity, column (3) adds interactions between various demographic variables and the time trend. Consistent with the results of California Plug-in Electric Vehicle Owner Surveys[22], our results show that MSA's with a higher share of college degree, white, Asian, and drive-to-work residents tend to have a higher rate of EV adoption. To capture potentially different impacts of charging network on BEV's and PHEV's, column (4) includes an interaction between the number of charging stations and an indicator variable indicating whether the vehicle is a BEV. The coefficient before the interaction term is negative, suggesting that the adoption of BEV's relies more on the charging network than that of PHEV's. However, this additional impact is not significant. Furthermore, to capture the heterogeneous impacts of charging networks across MSA's with different commuting time, column (5) includes an interaction between the number of charging stations and an MSA's average commute time to work. The negative coefficient on the interaction term suggests that the effect of charging stations on EV adoption is stronger among MSA's with longer average commute time. This is consistent with our intuition that in MSA's with a longer commute time, range anxiety is a more serious concern and hence the charging station network plays a more important role in EV adoption decisions.[23]

To examine whether our results are robust to the instrumental variable used in our baseline specification, columns (6) and (7) use alternative instrument variables: whether the MSA is a participant of the Northeast Network which is a government-sponsored effort to build charging stations, local tax credits for building charging stations, and the availability of

[22] Based on the survey results, 90% of the EV owners have college degree or above, 95% of the EV owners also own a conventional fuel vehicle but they drive the EV for 90% of the work commute.

[23] The importance of the charging network may vary across areas within an MSA with different population densities and demographics. Our data is aggregated at the MSA level and lacks the spatial resolution to construct the density of EV owners by demographics at a finer geographic level. Further exploring the spatial heterogeneity is an interesting question for further research.

public funding for building charging stations. These three variables appear in the charging station supply equation. However, we do not use them as IVs in our baseline specification because those subsidies could be a response to unobserved EV demand shocks and hence the exogeneity assumption may not hold. Nevertheless, our baseline results are robust to the inclusion of those additional IV's.

Nested Logit Model

In our baseline specification, we use $ln(1-s_{jmt})$ as the dependent variable following the theoretical model. However, the parameter estimates do not have straightforward interpretations. To follow the discrete choice models with market-level data (see Berry 1994 and Rysman 2004), we estimate a nested logit model that allows for a richer and more reasonable substitution pattern among the choices. We define all the EV models in one nest and the other choices (i.e., gasoline vehicles or no-purchase) as the other nest:

$$ln(s_{jmt}) - ln(s_{0mt}) = \beta_0 + \beta_1 ln(N_{mt}) + \beta_2 ln(p_{jmt}) + \sigma ln(s_{jmt|EV}) + \beta_3' X_{jmt} + \vartheta_{jmt}, \tag{13}$$

where s_{jmt} is the market share of model j in MSA m in year-quarter t and s_{0mt} is the market share of other choices. $s_{jmt|EV}$ is the within-group share: the share of EV model j among total EV sales. The parameter σ measures the correlation in unobserved utility (to the econometrician) from different EV models. As σ goes to one, the correlation across EV models within the nest goes to one. When σ is zero, the specification becomes the logit model that exhibits the IIA property.

This specification has three endogenous variables: $ln(N_{mt})$, $ln(p_{jmt})$, and $ln(s_{jmt|EV})$. Following the strategy in the baseline demand equation, we instrument for $ln(N_{mt})$ using the interaction between log(number of grocery stores at the end of 2012) and log(total number of charging stations in last quarter across all MSA's), and instrument for $ln(p_{jmt})$ with the difference between the automaker's CAFE target and its actual fuel economy in the previous year. $ln(s_{jmt|EV})$ is endogenous because it is a function of $ln(N_{mt})$ and $ln(p_{jmt})$. Conceptually, the coefficient on the within-group share σ can be identified by the variation of the EV group's share due to changes in the number of EV models or EV attributes (including both observed and unobserved). To deal with the endogeneity in the within-group share, we instrument for $s_{jmt|EV}$ using the interaction between the market share of the car manufacturer that produces model j in that MSA before the introduction of EV's in the U.S. (denoted as s_{jm0}) and the national sales of model j at time t (denoted as q_{jt}). The intuition behind this IV strategy is that national shocks to an EV model could have different impacts on its sales across MSA's: the MSA's in which the automaker has a larger market share (of conventional gasoline vehicles) before the introduction of EV's will be affected by national shocks more than others, for example due to better name recognition and dealer networks. To construct the variable s_{jm0}, we collect the total sales by car manufacturer by MSA by year from 2007 to 2010. Table B.I in the web appendix reports the first-stage results of the nested logit specification. It shows that the coefficient estimate of the interaction term is 0.196 (with a standard error of 0.055), suggesting that a larger market share in the gasoline vehicle segment (pre-EV introduction) is associated with a larger EV market share.

The estimation results of the nested logit model are reported in Table V. The first two columns are a simple logit model without the within-group share. The first column does not address any endogeneity issues while the second column instruments for $ln(N_{mt})$ and $ln(p_{jmt})$. Columns (3) to (5) reports the results of with instruments for $ln(N_{mt})$, $ln(p_{jmt})$, and $ln(s_{jmt|EV})$. Column (4) adds the interaction between the number of stations and the average commute time to work. Column (5) adds another three instruments for $ln(N_{mt})$ including whether an MSA participates in the Northeast Network, local tax credits, and availability of public funding for building charging stations.

The coefficient before $ln(N_{mt})$ is positive and statistically significant across all specifications, confirming the presence of positive indirect network effects in an alternative empirical framework. The elasticity with respect to the charging network is $\frac{\partial s_{jmt}}{\partial N_{mt}}\frac{N_{mt}}{s_{jmt}} = \beta_1\left(\frac{1}{1-\sigma} - \frac{\sigma}{1-\sigma}s_{jmt|EV} - s_{jt}\right)$, which is 2.978 based on the results of our preferred specification - column (3). That is, the market share of EV's would increase by 2.978% if the number of charging stations increases by one percent. The average own-price elasticity is −1.024, which is lower than the estimates in the literature that studies the gasoline vehicles.[24] This is likely due to the fact that electric vehicles are more expensive than an average gasoline vehicle and EV buyers are richer and less price sensitive than gasoline vehicle buyers. In addition, early adopters of EV's may choose to buy EV's for environmental concerns and pay less attention to the price factor.[25]

The logit and nested logit models lump non-EV models and no-purchase together as the outside option. This assumes that the substitution between the non-EV's and EV's is the same as the substitution between no-purchase and EV's. This obviously is a restrictive assumption. In an alternative specification, we construct the market share using the number of new vehicles sold in a market instead of the number of potential buyers as the

[24] The average own-price elasticity is −5.4 in Berry *et al.* [1995] and −1.97 for new cars in Bento *et al.* [2009].

[25] California Plug-in Electric Vehicle Owner Survey (2014) shows that among buyers of new gasoline vehicles, 15% of the households have an annual household income over $150,000 while it is 54% among EV buyers (https://energycenter.org/clean-vehicle-rebate-project/vehicle-owner-survey/feb-2014-survey). In addition, the environmental concern is an important motivation behind EV purchase: 38% of Nissan Leaf buyers and 18% Chevy Volt buyers consider the environmental concern to be their top motivator.

TABLE V
EV DEMAND EQUATION: LOGIT AND NESTED LOGIT MODEL

	(1)	(2)	(3)	(4)	(5)
	Logit	IV	IV	IV	IV
ln(No. of charging stations)	0.387***	1.387***	1.419***	−5.702***	1.335***
	(0.043)	(0.166)	(0.161)	(1.145)	(0.144)
ln(stations)*ln(commute time)				2.091***	
				(0.346)	
ln(EV price)	−1.334***	−1.568***	−0.488**	−0.271**	−0.285**
	(0.122)	(0.238)	(0.292)	(0.131)	(0.152)
ln(gasoline price)*BEV	0.664***	0.642**	0.858***	0.815***	0.858***
	(0.240)	(0.271)	(0.291)	(0.276)	(0.284)
ln(gasoline price)*PHEV	0.438**	0.282	0.412	0.363	0.427
	(0.210)	(0.248)	(0.284)	(0.270)	(0.277)
ln(residential charging	0.020	−0.097**	−0.113**	−0.114***	−0.105**
from EV project)	(0.037)	(0.047)	(0.048)	(0.039)	(0.047)
HOV exemption for EV's	0.122**	0.160	0.256*	0.229**	0.256*
	(0.062)	(0.131)	(0.155)	(0.098)	(0.144)
ln(household income)	3.195***	3.980***	2.972*	2.523**	2.766*
	(1.193)	(1.427)	(1.535)	(1.196)	(1.444)
$ln(s_{jmt\|EV})$			0.630***	0.723***	0.685***
			(0.143)	(0.108)	(0.018)
MSA-model FE	Y	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y	Y
IV for ln(No. of stations)	N	Y	Y	Y	Y
IV for ln(EV price)	N	Y	Y	Y	Y
IV for ln(within-group share)	–	–	Y	Y	Y
Over identification test					0.0298
Under identification test				0.0000	0.0000
Observations	13,485	13,197	12,941	12,941	12,941

Notes: The dependent variable is $ln(s_{jmt})-ln(s_{0mt})$. From column (2) to (5), the IV for EV price is the difference between a car manufacturer's CAFE standard and its actual fuel efficiency last year. From column (2) to (4), the IV for $ln(N_{mt})$ is the interaction between log(number of grocery stores at the end of 2012) and log(total number of charging stations in last quarter across all MSA's), and in column (5) we add three other instruments including whether a MSA participates in the Northeast Network, local tax credits and availability of public funding for building charging stations. From column (3) to (5), we instrument $ln(s_{jmt|EV})$ with the product between the automaker's market share in the local market before 2011 and the model's current national sales. Clustered standard errors at the MSA level are in parentheses.

$^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

denominator. This allows no substitution between the no-purchase and EV's but substitution between non-EV's and EV's. We obtain very similar results. The logit and nested logit specifications produce a restrictive substitution pattern across different (EV and non-EV) models. In theory, the substitution pattern across vehicle models is identified by the variation in market shares due to the changes in the choice set and product attributes over time or across markets. However, due to the short time span of our data, the substitution pattern across models would be hard to identify empirically with only market-level sales data. This paper focuses on characterizing the aggregate market equilibrium outcomes and the critical mass issue due to the interdependence of EV adoption and charging station investment for which the market-level sales data should be appropriate.

IV(iv). *Charging Station Supply Equation*

The issue of endogeneity due to simultaneity also arises in equation (12): the installed base of EV's, $ln(Q_{mt})$ could be correlated with the error term ω_{mt}. To address the endogeneity, we instrument $ln(Q_{mt})$ with the gasoline prices in the current quarter and annual gasoline prices in past years. The fuel cost savings from driving EV's depend on the price difference between gasoline and electricity, which varies across locations and over time. Consumers in MSA's with higher gasoline prices may have a stronger incentive to purchase EV's.

We argue that gasoline prices are unlikely to affect charging station investors' investment decisions directly (i.e., other than through the EV installed base). Since we include both time and MSA effects, the remaining variation in gasoline prices is largely driven by how time-varying crude oil prices interact with local market conditions that are likely time-invariant during our data period (e.g., market structure in wholesale and retail gasoline markets and distance to refineries). These interactions lead to time-varying and MSA-specific differences in gasoline prices, which are unlikely to be correlated with charging station investment decisions. As outlined in the stylized model, the net benefit of building charging stations depends on the EV market potential (proxied by the installed base of EV's) and the costs of investment. Fixed costs include the cost of equipment (chargers) and labor cost, neither of which is likely to be correlated with gasoline price variations (after controlling for MSA and time fixed effects). The operating costs of the charger largely depend on electricity prices which are not directly related to gasoline prices (after controlling for common shocks such as national economic conditions).

Table VI reports the first-stage results of the charging station supply equation. The dependent variable is log (EV installed base) in an MSA in a year-quarter. We use a set of MSA-level gasoline prices (in the same

TABLE VI
FIRST-STAGE RESULTS OF THE STATION SUPPLY EQUATION

	(1): $ln(Q_{mt})$		(2): $ln(Q_{mt})$	
ln(current gasoline price)	0.713**	(0.288)	0.624**	(0.278)
ln(gasoline price last year)	4.263***	(1.121)	4.252***	(1.122)
ln(gasoline price two years ago)	2.387***	(0.893)	2.491***	(0.881)
ln(gasoline price three years ago)	3.390***	(1.037)	3.996***	(1.034)
EV purchase incentives			0.116***	(0.036)
Northeast network	0.116	(0.103)	0.038	(0.104)
ln(change of installation cost)	−0.026	(0.072)	−0.080	(0.073)
Public funding	−0.291***	(0.080)	−0.296***	(0.079)
R^2	0.882		0.884	
Observations	3894		3894	

Notes: The dependent variable is log(EV installed base). Clustered standard errors at the MSA level are in parentheses.

*p<0.10, **p<0.05, ***p<0.01.

quarter, last year, two years ago, and three years ago) as the instrumental variables. The estimates of coefficients before gasoline prices are all significantly positive, confirming that consumers in MSA's with higher gasoline prices are more likely to purchase EV's.

The first two columns of Table VII report the OLS estimation results of the charging station supply equation, where the first column does not include year-quarter fixed effects and the second column includes those time effects. To deal with the endogeneity of the EV installed base, we use various instrumental variables and report the results in the remaining columns of Table III. In particular, the third column uses the EV purchase incentives (tax credits and rebates at the federal and state levels), the fourth column uses a set of gasoline prices (the current gasoline price, average gasoline price last year, average gasoline price two years ago, and average gasoline price three years ago), and the last column uses both EV purchase incentives and gasoline prices. All regressions provide positive and statistically significant coefficients before the EV installed base, ranging from 0.285 to 0.671. The positive sign suggests that a larger installed base of EV's attracts more investors of charging stations. We take the fourth column as our baseline specification due to the concern that the EV purchase incentives (especially those at the state level) could be endogenous as they could be a response to the unobserved shocks to the supply of charging stations.

The coefficient before the charging station installation cost is negative but insignificant, implying that investors are less likely to build charging stations if the cost is high. The coefficient before the Northeast Network is positive and significant, implying that investors are more likely to invest

TABLE VII
CHARGING STATION SUPPLY EQUATION

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	IV	IV	IV
ln(EV installed base)	0.307 ***	0.285 ***	0.450 **	0.671 ***	0.565 ***
	(0.010)	(0.025)	(0.209)	(0.162)	(0.120)
ln(change in installation cost)	-0.036	-0.024	-0.023	-0.023	-0.023
	(0.152)	(0.154)	(0.150)	(0.146)	(0.148)
Participating in NEVN	0.442 ***	0.385 ***	0.352 ***	0.308 ***	0.329 ***
	(0.093)	(0.097)	(0.100)	(0.100)	(0.095)
Public funding for stations	0.016	-0.042	0.005	0.068	0.038
	(0.058)	(0.057)	(0.083)	(0.079)	(0.069)
MSA fixed effects	Y	Y	Y	Y	Y
Year-quarter FE	N	Y	Y	Y	Y
Over identification test			0.0000	0.5861	0.5205
Under identification test			0.0382	0.0010	0.0005
Observations	3894	3894	3894	3894	3894

Notes: The dependent variable is log(number of charging stations). The observations are for 354 MSA's for 11 quarters from 2011 to the third quarter of 2013. The instrument variable for Column (3) is the EV purchase incentives (tax credits and rebates at the federal and state levels). The instrument variables for Column (4) include a set of gasoline prices (including the current price, average price one year ago, average price two years ago and average price three years ago). The instrument variables for Column (5) are EV purchase incentives and gasoline prices. Clustered standard errors at the MSA level are in parenthesis.
$^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

in the areas that are members of the Northeast Network. As we discussed before, this is because this Network would reduce the investment cost.

V(i). *Steady-State Equilibrium*

Based on the estimates of our baseline model (Column 4 of Table III and Column 4 of Table VII), we simulate the long-run equilibria for each of 354 MSA's. An important caveat of the simulation is that the market conditions for both EV demand and charging station supply (such as the number of EV models, EV prices and household income etc.) are kept the same as in the third quarter of 2013 except that the stock of EV's and the number of charging stations evolve over time. Our goal here is to understand the equilibrium properties under given (e.g., the 3rd quarter in 2013) market conditions.[26]

[26] The quarterly scrappage rate is set to be 1/36 because the expected lifetime of a vehicle is nine years according to the 2001 U.S. National Household Travel Survey (NHTS), also see Chen *et al*. [2013].

V(ii). *Steady-State Equilibrium*

The total EV adoption in all 354 MSA's without subsidy in the steady state would be 1.14 million units, an almost ten-fold increase from the 116,448 units by the third quarter of 2013.[27] However, the share of EV's among the total vehicle stock would still only be about one per cent. This small share critically depends on the market conditions observed in the 3rd quarter of 2013. Since more EV models are slated to come to the market and EV prices continue to drop, the EV stock in the steady state is likely to be larger than what our simulations predict. Nevertheless, our results suggest that the penetration of the EV technology faces significant challenges going forward.

Our simulation results indicate that the levels of steady-state EV adoption are substantially heterogeneous across MSA's. Among these 354 MSA's, 13 of them (4%) have no positive equilibrium (case I), 215 of them (61%) have two positive equilibria and hence the critical mass issue (case II), and 126 of them (36%) have only one positive equilibrium (case III).

Our theoretical analysis suggests that the equilibrium outcome of a market depends on EV prices, market characteristics affecting consumer preference and the profitability of charging stations. Table VIII provides the average market characteristics of the three groups of MSA's, including population, gasoline prices, household income, share of college educated, share of white, share of Asian, and average commute time to work. As shown in Table VIII, those demographics are lowest among the no-positive-equilibrium MSA's (case I), highest among the one-positive-equilibrium MSA's (case III), and in between among the critical-mass constrained MSA's (case II). Although the MSA fixed effects in our baseline specification absorb these demographics, the pattern bodes well with our intuition that those demographics are positively correlated with consumers' preference for EV's and investors' profit from charging stations.

The average EV stock per million people in the steady state is 4,709, compared to 481 in the 3rd quarter of 2013. The range of steady-state EV stocks across MSA's is from 0 to 24,565 per million people, compared to the range of 23 to 4,312 in the 3rd quarter of 2013. Among the 126 MSA's with positive adoption in the steady state, 12 of them (10%) have fewer than 1,000 units per million people, 82 of them (65%) have between 1,000 to 10,000 units per million people, and 32 of them (25%) have more than 10,000 units per million people. Table B.II in the web appendix reports the top ten MSA's in terms of total EV adoption and EV adoption per million people, respectively. Most of the MSA's with the highest adoption are in California.

[27] The EV stock does not increase after 154 quarters. That is, the long-run equilibrium is achieved for each of the MSA's after that.

TABLE VIII
MARKET CHARACTERISTICS BY EQUILIBRIUM TYPES

	Case I: No positive equilibrium	Case II: Critical mass	Case III: One positive equilibrium
Number of MSA's	13	215	126
Population	126,191	651,867	797,261
Gasoline price	\$3.56	\$3.57	\$3.68
household income	\$39,492	\$39,551	\$42,619
% college degree	35%	38%	41%
% white	77%	78%	82%
% asian	1%	2%	4%
Commute time to work	20 min	22 min	23 min

In these MSA's, the EV adoption per million people would be more than 15,000 units, three times the average.

The simulations of the steady-state equilibrium are based on the market conditions present in the 3rd quarter of 2013. However, more and more EV models came onto the market after 2013, and these are not included in our data. To account for the recent developments of the EV market, we simulate the steady-state EV adoption by setting the number of EV models at the end of 2016 level in alternative simulations.[28] Our simulation results indicate that the total steady-state EV adoption would be 2.71 million. Among all 354 MSA's, 22 MSA's belong to the case I (no positive equilibrium), 201 MSA's belong to the case II (critical mass), and the remaining 131 MSA belong to the case III (one positive equilibrium). Overall, the distribution of equilibrium types is similar to that of the benchmark simulation and more than half of the MSA's face the critical mass constraint.

V(ii). *Role of Indirect Network Effects*

To examine the impact of indirect network effects on EV adoption, we simulate the steady-state EV adoption with varying magnitude of indirect network effects from charging station availability on EV adoption (i.e., $\hat{\beta}_1$) by making the magnitude proportional to the estimated indirect network effect while holding everything else constant. The results are reported by Figure 3.

First, the steady-state EV adoption is increasing and convex in β_1 because of the positive feedback effects. Second, kinked points exist because some MSA's switch from zero adoption to positive adoption as β_1 increases, leading to a discontinuous increase in the EV adoption. Third, the EV adoption

[28] See the website of AFDC: https://www.afdc.energy.gov/data/widgets/10567.

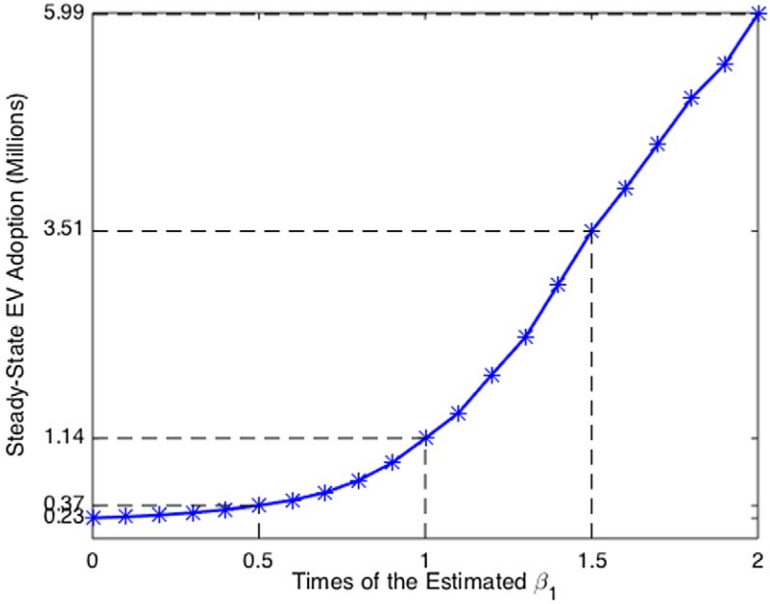

Figure 3
Steady-State EV Adoption with Varying β_1
[Colour figure can be viewed at *wileyonlinelibrary.com*]

is 0.23 million when $\beta_1 = 0$ (20% of the EV adoption predicted by the estimated value), implying that the indirect network effect accounts for 80% of the EV stock in the steady state.

VI. POLICY SIMULATIONS

Our theoretical analysis suggests that the impact of a government subsidy policy depends on the model parameters that characterize the strength of the indirect network effects, consumer preference and investors' profitability from building charging stations. In this section, we first quantify the impact of current federal subsidy policy and then examine alternative policies that target the 215 MSA's with the critical mass constraint.

VI(i). *Impact of Federal Subsidy Policy*

We have discussed the qualitative impact of a permanent price cut in Section III(vi). In practice, the $7,500 income tax rebate has a phase-out period - once an EV manufacturer sells the first 200,000 EV's, the subsidy will end for that automaker. A similar phase-out period was implemented for hybrid vehicles in the early 2000's. To examine the impact of such a temporary subsidy policy, we simulate the EV adoption if government provides EV buyers a tax credit of \$7,500 until one-fourth of the total \$7.5 billion budget (i.e., around 1.875 billion dollars) is exhausted.

This temporary policy would contribute 244,048 additional EV's in the steady state, amounting to 21.4% of the total adoption in the absence of any subsidy. This implies a unit cost of \$7,683 for the induced EV adoption through the policy. Figure 4 plots the EV adoption and EV sales over time under the subsidy policy. The budget would be exhausted after twelve quarters. However, this impact would not stop immediately after the policy expires; instead, it would gradually diminish to its steady-state level due to feedback effects.

The policy impact comes from two sources. First, among those 126 MSA's that would have positive adoption in the steady state even if there were no subsidy (Case III), their EV sales and hence the installed base during the subsidy period would increase. However, this impact would gradually diminish to zero after the subsidy expired. As shown in Figure 5(a), the impact reaches its peak when the budget is exhausted in quarter 12, inducing 3,524 (18%) sales during that quarter. For those positive-adoption MSA's, the subsidy policy would contribute 54,811 EV sales in total but have no impact on their steady-state adoption levels.

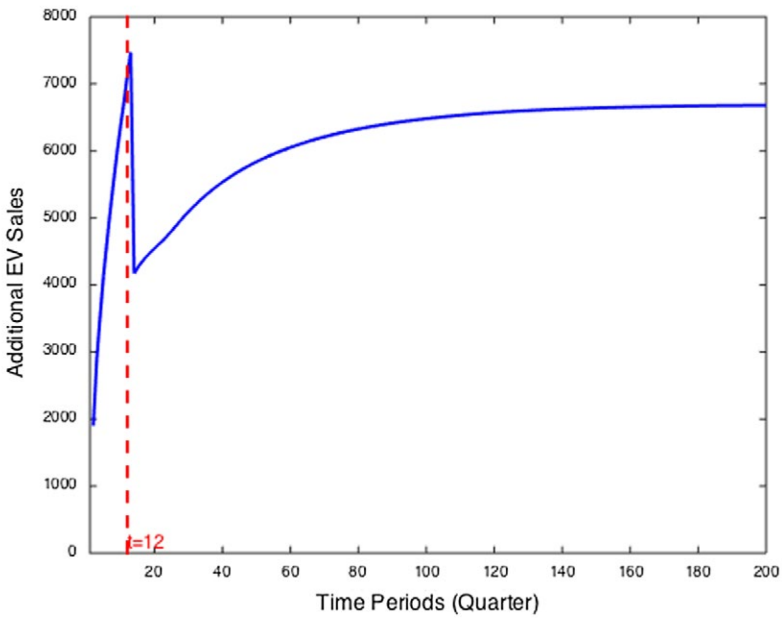

Figure 4
Additional EV Sales with the Federal Income Tax Credits
[Colour figure can be viewed at *wileyonlinelibrary.com*]

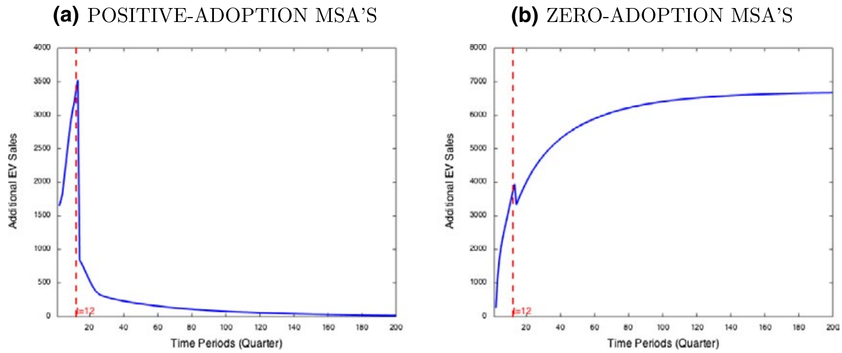

Figure 5
Decomposition of the Policy Impact
Notes: Figure (a) plots the additional EV sales over time for the 126 MSA's that would have positive adoption in the steady state even without subsidy. Figure (b) plots the additional EV sales over time for the 33 MSA's that have zero adoption in the steady state without subsidy but have positive adoption in the steady state under the federal income tax credit policy
[Colour figure can be viewed at *wileyonlinelibrary.com]*

Second, 33 MSA's would have no adoption in the steady state without subsidy but with the \$7,500 subsidy per EV, they could successfully pass the critical mass constraints and have positive adoption in the steady state. Figure 5(b) plots the subsidy-induced sales of these MSA's over time. The policy-induced sales increase to 3,949 units when the budget is exhausted, drop to 3,330 units after that quarter, and gradually increase to 6,711 units every quarter in the steady state.

(ii). *Policies Targeting Critical-Mass Constrained MSA's*

Our analysis above shows that in the absence of any subsidy, 215 MSA's would face critical mass constraints. The federal subsidy policy that is currently implemented provides the same amount of subsidy per unit of EV sales across all MSA's. For the same MSA's, the current subsidy amount is not enough to help them pass their critical mass constraints and as a result they would not have any adoption in the steady state. This may not be optimal in terms of promoting EV adoption in the long run. In this section, we examine alternative policy designs that exploit market heterogeneity by targeting these critical-mass constrained MSA's.

(*A*). *Fixed Subsidy Amount per EV*

We first consider policies that impose a fixed amount of subsidy per EV to all critical-mass constrained MSA's until a pre-designated budget is

TABLE IX
IMPACTS OF FIXED-UNIT-SUBSIDY POLICIES

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
	$2,500	$5,000	$7,500	$10,000	$15,000	$20,000	$25,000
No. of successful MSA's	4	18	33	43	82	125	102
No. of reverted MSA's	0	0	0	5	9	14	109
No. of subsidy quarters	773	85	50	27	14	8	2
Steady-state EV stock	32,862	196,942	244,048	406,331	605,623	706,470	577,500
Cost per induced EV ($)	57,057	9,521	7,683	4,614	3,096	2,654	3,247
EV sales of the last subsidy quarter	968	5,652	6,813	10,426	14,956	18,334	41,410
Total sales during subsidy periods	750,483	376,435	250,901	196,693	138,252	98,628	79,164
Steady-state sales	904	5,416	6,711	11,174	16,655	19,428	15,881

Notes: The successful MSA's are those that would surpass the critical mass constraint even after the subsidy policy expires and grow towards their high-adoption equilibrium in the steady state. The reverted MSA's includes those that can surpass the critical mass constraint with continued subsidy but revert to the origin after the subsidy expiration. The number of subsidy quarters is the number of quarters before the subsidy budget is exhausted. Subsidy cost per induced EV is the cost per unit adoption included by the policy, measured by the ratio of total budget over the total EV adoption in the steady state.

exhausted. To make it comparable to the current federal income tax credit policy, we assume that the budget is \$1.875 billion.

Table IX Column III reports the results of a policy that provides a subsidy of \$7,500 for each eligible sale in those critical-mass constrained MSA's until the total subsidy reaches \$1.875 billion. The subsidy would last for 50 quarters and 33 MSA's would successfully surpass the critical mass constraints and converge to the high-adoption equilibrium in the steady state. This policy would generate 244,048 EV adoptions in the steady state and hence the average cost of each adoption induced by the policy in the steady state would be \$7,683. Compared with the current \$7,500 federal policy that applies to all MSA's, this alternative policy has the same impact on EV adoption in the steady state. This is because temporary subsidy policies would not affect the EV adoption of those positive-adoption MSA's in the steady state. With a \$7,500 unit subsidy, the same set of MSA's would surpass the critical mass constraint even though the subsidy durations are different. As a result, the impact on total EV adoption in the steady state is the same. However, the paths of impact on EV sales are quite different under these two designs. The alternative policy would increase EV sales by 250,901 in total before the subsidy expires. The EV sales in each quarter would increase to 6,813 units during the subsidy periods, drop slightly when the subsidy expires, and converge to the steady-state level of 6,711 units.

Table IX also reports the results of several other designs with the subsidy amount varying from \$2,500 to \$30,000 per eligible sale. As the subsidy becomes more generous, the budget would be exhausted sooner and more MSA's would revert to the origin after that. Take the policy of \$20,000 per unit subsidy for example. 139 MSA's would grow toward the critical mass point due to the subsidy. However, the budget would be used up after eight quarters. After that, fourteen MSA's would revert to the origin and the remaining 125 MSA's would continue to converge to their high-adoption equilibria. The subsidy cost per EV adoption induced by the policy would be only \$2,654, compared to \$7,683 under the current policy.

When the subsidy is below \$20,000, more MSA's would successfully surpass the critical mass constraint as the subsidy increases. As a result, the total EV stock of those MSA's in the steady state would increase from 32,862 to 706,470 and the subsidy cost per EV adoption would decrease from \$57,057 to \$2,654. However, when the unit subsidy is very high (e.g., \$25,000), the budget would be exhausted very quickly, many MSA's would revert to the origin after the budget expires, and fewer MSA's could actually successfully move towards the high-adoption equilibrium in the steady state. As a result, the ratio of budget over the steady-state EV adoption would be high again. The last three columns illustrate the tradeoff in terms of steady-state sales between the unit subsidy amount and the subsidy duration.

TABLE X
IMPACTS OF FIXED-DURATION POLICIES

	(I)	(II)	(III)
	One year	Three years	Five years
No. of MSA's with minimal required subsidy			
below \$5,000	13	16	17
below \$10,000	41	43	44
below \$15,000	78	86	88
below \$20,000	132	135	139
below \$25,000	201	215	215
below \$30,000	215	215	215
Average unit subsidy across all critical-mass MSA's (\$)	16,526	15,769	15,662
Steady-state EV stock	974,337	974,337	974,337
Total subsidy (billions \$)	0.399	2.088	4.138
Cost per induced EV(\$)	410	2,144	4,251

(*B*). *Fixed Subsidy Duration*

We next consider policies that impose a spatially-differentiated subsidy to those critical-mass constrained MSA's for a fixed duration to help them to surpass the critical mass. Such localized subsidy policies can be carried out by state or local governments. Federal agencies such as the DOE have been providing grants to local jurisdictions (e.g., Northeast Electric Vehicle Network) and privates sectors (e.g., Actuality) to target specific areas.[29]

Table X Column I reports the results of a one-year policy. For each critical-mass constrained MSA, we first calculate the minimal subsidy amount that is needed to surpass its critical mass constraint within one year. Our results suggest that 13 MSA's require no more than a \$5,000 subsidy per unit sale, 41 MSA's require no more than \$10,000 subsidy per unit sale and all other MSA's require a higher level of subsidy. The average subsidy amount across all critical-mass constrained MSA's would be \$16,526 per unit of sales. The one-year policy is designed to subsidize the minimal required amount for each critical-mass constrained MSA so that they can successfully surpass the critical mass within one year. We show that this policy would generate 0.974 million EV stock in the steady state and would cost \$0.399 billion in total. The average cost of each steady-state adoption induced by the policy would be \$410 per EV.

[29] In the market for local telephone service, Fan and Xiao [2015] show that policymakers could exploit market heterogeneity by targeting smaller markets when designing subsidy policies to encourage entry and reduce incidences of monopoly.

TABLE XI
IMPACTS OF FIXED-DURATION POLICIES WITH $15,000 LIMIT

	(I)	(II)	(III)
	One year	Three years	Five years
No. of MSA's with minimal required subsidy			
below $5000	13	16	17
below $10000	41	43	44
below $15000	78	86	88
Average unit subsidy across all critical-mass MSA's ($)	8,988	8,922	8,943
Steady-state EV stock	618,577	625,822	626,260
Total subsidy (billion $)	0.080	0.540	1.181
Cost per induced EV($)	130	863	1,886

Table X also reports the results for similar policies with a duration of three years and five years. As the subsidy duration increases, the required subsidy amounts of all MSA's would decrease, but not dramatically. Meanwhile, the total adoption in the steady state would not be affected. Therefore, the policy-induced cost of each steady-state adoption would increase. These results suggest that under the given market conditions, a more generous subsidy with a shorter duration (and a fixed budget) is more cost-effective than alternative designs.

Since a subsidy above $15,000 per unit sale is likely to be unrealistic in practice, we also simulate the EV adoption path by excluding those MSA's with a minimal required subsidy above that amount. Table B.II reports the results. The comparison of different policy designs points to the same finding that a more generous subsidy (but a shorter duration) is more effective in pushing the MSA's to surpass the critical mass constraints and achieve the high-adoption equilibrium.

When we extend the subsidy duration, there are two countervailing forces that affect the total subsidy expenditure. On the one hand, the minimal subsidy amount such that an MSA can surpass its critical mass goes down, that is, the per-unit subsidy decreases. This would reduce the total subsidy expenditure. On the other hand, because all sales occurring during the subsidy period qualify for the subsidy, more units would be eligible to receive the subsidy when the duration extends, which would increase the total subsidy expenditure. The impact of extending subsidy duration is ambiguous in theory. However, as shown in Table X, the minimal subsidy per unit sold decreases only slightly when we extend the duration. In other words, the second effect dominates, leading to the steep rise in the cost per induced EV when we extend the subsidy duration.

(*C*). *Discussion*

Under fixed-subsidy policies, not all MSA's could successfully surpass the critical mass constraints and move towards the high-adoption equilibrium. In general, except for very high subsidy amounts, as the per-unit subsidy increases, more MSA's can surpass the constraint and generate more EV adoption in the steady state. For fixed-duration policies, on the contrary, each MSA is subsidized with the minimal required amount that is needed to surpass its critical mass constraint. Thus, regardless of the duration of the subsidy, all MSA's would successfully move towards their high-adoption equilibrium and hence generate the same amount of EV adoption in the steady state (0.974 million units). As a result, this spatially differentiated policy that explicitly addresses the critical mass issue is more cost-effective as measured by the (government) cost per induced EV in the steady state.

California Air Resources Board designed the zero-emission vehicle (ZEV) mandates. Under the ZEV mandates, an automaker's zero-emission vehicle sales have to account for a certain percentage of all of its new vehicle sales, and this percentage requirement increases over time −2% for model year 2016, 4.5% for model year 2018, and 22% for model year 2025. The ZEV sales requirement is administered through a tradable credit system. Each qualified new vehicle sale can generate credits for automakers and the value of the credits depends on certain vehicle characteristics including, for example, the electric driving range of electric vehicles. The program is expected to encourage the sales of vehicles powered by electricity or hydrogen fuel cells. By 2016 nine other states, including Oregon and eight Northeast states, have also chosen to follow California's ZEV mandates and collectively proposed steps to reach this goal including aligning building codes to make it easier to build charging stations and providing cash incentives for ZEV's buyers.[30] Three other states - Washington, Delaware, and Pennsylvania - are following California's Low Emission Vehicle (LEV) program, but not the ZEV program at present. While our analysis suggests that this level of adoption under the ZEV mandate or LEV program would necessitate that market conditions (e.g., supply and demand factors) significantly improve, state and local governments could pay attention to market

[30] The ten states with ZEV mandates include California, Connecticut, Maine, Maryland, Massachusetts, New York, Oregon, Rhode Island and Vermont.

heterogeneity by designing localized policies to address the critical mass issue exhibited in many of the MSA's.

Despite the improved cost-effectiveness of the alternative policy, the total EV stock across the MSA's in the long-run equilibrium would only amount to about one per cent of the vehicle stock. As more and more EV models enter the market and the EV prices go down over time, the EV adoption in the long-run would certainly surpass the level suggested by our simulation results.

In addition, BEV consumers value the public charging stations more than PHEV consumers do, as shown by the forth column of Table IV. To account for the different level of reliance on charging stations between BEV's and PHEV's, we use the estimates of that specification and simulate the stead-state EV adoptions for the subsidy policies we have considered. The results are reported in Table B.III in the Appendix. As expected, subsidy policies have larger impacts on BEV's than PHEV's due to the stronger indirect network effects between BEV adoption and charging stations deployment.

VI(iii). *Caveats*

Our empirical analysis and simulations are based on a stylized model of EV demand and charging station investment. We now discuss the underlying assumptions and their implications on our results. First, we assume that the pool of new potential consumers is the same every quarter. However, early adopters are likely to have a higher valuation of EV's and a lower sensitivity to price. After those early adopters make their purchases and leave the market, the new buyers for EV's may be more price sensitive. Therefore, subsidies for these consumers in the future would be more effective in terms of stimulating EV adoptions. That is, the policy impacts in later periods could be larger than that of the earlier years. In addition, the total subsidy expenditure may not rise as quickly as what our model has predicted.

Second, our demand model is static and does not incorporate consumer forward-looking behavior. On the one hand, forward-looking consumers may purchase EV's earlier than otherwise if they expect that the (temporary) subsidy will end in the near future. Therefore, the demand model ignoring the forward-looking behavior could overestimate consumer price sensitivity (i.e., mistaking the forward-looking behavior as the short-term response to subsidy) and the short-term impact of temporary subsidy policies. On the other hand, to the extent that consumers expect EV prices to fall over time, for example due to technological improvement, they may have an incentive to postpone their purchase. Without taking this into account, the model could underestimate consumer price sensitivity (i.e., mistaking the forward-looking behavior as the lack of response to subsidy) and the policy impact.

Third, our analysis assumes that EV adoption is affected by the charging station network in the same MSA but not by those in other MSA's. To the extent that some consumers travel across MSA's, the network outside of the MSA could matter. Given that local (within-MSA) driving accounts for the majority of driving and EV's tend to be the secondary vehicle in the household, we focused on the stations in the local MSA. As more and more EV's become the primary vehicle and more long-distance travel is being carried out in these vehicles, the larger network of charging stations could matter more. Li *et al.* [2017] focuses on the supply side of the charging stations and allows both local travel and long-distance travel between cities. Both the local charging network and traversability across cities (as a function of the battery range and charging network) are incorporated in the utility function.

Fourth, our long-run simulations do not take into account the emerging technologies in the automobile sector such as autonomous vehicles. Autonomous vehicles could change the travel pattern, for example by increasing the total distance traveled, since they reduce the opportunity cost of driving. In the long run this could affect household location choices and urban structure. This type of technology has the potential to dramatically change the landscape of vehicle ownership and driving behavior, but modeling them would necessitate additional assumptions and data and is beyond the scope of our current analysis.

Fifth, although we account for the demand heterogeneity across EV models and MSA's by including the MSA-model fixed effects in the EV demand equation, we do not model the heterogeneity across stations and only use the total number of stations in an MSA to capture the impact of charging stations on EV demand in our estimation. Nevertheless, the impact of charging stations could exhibit spatial heterogeneity in that stations closer to major commuting routes may be more important than others. The optimal location of the station network is an important question. We abstract away in this dimension because analyzing an entry model with heterogeneous firms would necessitate a different framework than an entry model with homogeneous firms, see Berry and Reiss [2007] for details. Nevertheless, ignoring station heterogeneity could have implications for policy simulations. It is likely that the investors might build stations in the most important (high-demand) locations first and then expand the network to other areas. That is, the impact of stations could diminish as the network expands due to the location choice of the stations. If so, our analysis could overestimate the long-run impact of subsidy policies.

Lastly, we do not model automakers' pricing and product launch decisions and as a result, our model does not provide a prediction about the pass-through rates of the subsidy policies for us to incorporate in simulations. In the context of hybrid vehicles, Sallee [2011] shows that both federal and state incentives for the Toyota Prius are fully captured by consumers. The reason for the full pass-through is that Toyota may have believed that charging higher prices while the subsidy was in place would reduce future demand since high current prices may lead consumers to expect high future prices and search frictions prevent consumers from learning true prices. This argument could be applied to other alternative fuel technologies such as EV's. However, to the extent that the pass-through to consumers may not be full, our simulations would overestimate the policy impacts on EV adoption.

VII. CONCLUSION

Electric vehicles as a new technology hold the potential to fundamentally change the transportation sector. The diffusion of EV's coupled with cleaner electricity generation from renewable energy sources can provide a promising pathway to dramatically reduce air pollution from on-road vehicles and strengthen energy security. Similar to many other markets for new technologies, the EV market exhibits indirect network effects that have important implications for market dynamics and equilibrium outcomes. In this paper, we provide the first theoretical and empirical analysis of equilibrium properties of this market, paying particular attention to the issue of critical mass and its implications for policy design.

We first develop a stylized theoretical model of a dynamic system of EV adoption and charging station investment with indirect network effects to examine indirect network effects and their impact on equilibrium properties. Our analysis shows that the equilibrium outcomes depend on the nature of the indirect network effects, consumer preferences, EV prices, and the profitability of charging stations. In the steady state, a variety of equilibrium outcomes can emerge, of which one exhibits multiple positive equilibria and the critical mass phenomenon. If either consumer adoption or investor participation is below the critical mass, the system will converge to the low-adoption equilibrium with zero EV's and charging stations.

Using detailed vehicle sales and charging station data by quarter by MSA from 2011 to 2013, our empirical analysis finds economically significant indirect network effects in the market across a variety of model specifications. Based on parameter estimates, our simulations under the prevailing market conditions observed in the third quarter of 2013 show several different market equilibrium outcomes across the 354 MSA's, with 215 of them exhibiting the critical mass. Our simulations suggest that significant government subsidy (e.g., over $15,000) is needed to push most of these MSA's to pass the critical mass constraint and move towards the high-adoption equilibrium. The current federal subsidy policy provides \$7,500 for EV buyers regardless of which MSA they reside in. We examine alternative policies that use an equal budget but focus on pushing the critical-mass constrained MSA's to pass the critical mass constraint. Our simulations show that this strategy could generate a much higher level of EV adoption in the steady state relative to the current policy.

Our findings illustrate the role of indirect network effects in affecting market dynamics in network goods and demonstrate the important implications of the critical mass constraint on designing policies to promote technology adoption. In the absence of first-best policies (e.g., the Pigouvian tax) to deal with significant externalities from gasoline usage, subsidies for consumer adoption of EV's are being employed in many countries to promote this (potentially) cleaner technology. Our analysis shows that a spatially-differentiated subsidy policy that tries to address the critical mass constraint is much more effective in promoting technology adoption. Although our analysis is in the context of the EV market, our findings on the issue of the critical mass constraint and its policy implications could be relevant to markets for other new technologies with indirect network effects (e.g., hydrogen vehicles).

APPENDIX A

ADDITION DISCUSSIONS ON THE THEORETICAL MODEL

A.1 Multiple EV Models

Our model can be modified slightly to accommodate the case of multiple EV models. With multiple EV models, the utility of a potential consumer from adopting a particular EV model j at time t is

$$u_{ijt} = \theta_i v(N_t) - p_{jt} + \epsilon_{ijt},$$

where p_{jt} is the price of model j at time t and ε_{ijt} is the consumer idiosyncratic taste which is assumed to follow standard Type I extreme distribution. Consumer i's surplus at time t can be written as

$$U_{it} = E_\epsilon[max_j\{u_{ijt}\}] = ln\left(\sum_j exp\{\theta_i v(N_t) - p_{jt}\}\right) = \theta_i v(N_t) - ln\left(\sum_j exp(p_{jt})\right).$$

Define $P_t = ln(\sum_j exp(p_{ijt}))$, we can get equation (1) in the main text.

A.2 Proofs of Propositions

Proof of Proposition 1

We first derive the conditions for the existence of critical mass. Note that the right-hand side (RHS) of equation (10) is constant in Q. The partial derivative of the left-hand side (LHS) of the equation (10) with respect to Q is

$$\frac{\partial LHS}{\partial Q} = -Q^{-\beta_1\gamma_1-1}\left[\beta_1\gamma_1+(1-\beta_1\gamma_1)\rho Q/\bar{q}\right],$$

which reaches its maximum $LHS_{max} = (1-\beta_1\gamma_1)^{\beta_1\gamma_1-1}(-\beta_1\gamma_1\bar{q}/\rho)^{-\beta_1\gamma_1}$ when $Q = \hat{Q} \equiv \frac{-\beta_1\gamma_1\bar{q}}{(1-\beta_1\gamma_1)\rho}$. Notice that $\hat{Q} > 0$ under the assumptions $\beta_1 < 0$ and $\gamma_1 > 0$.

The second derivative of the LHS with respect to Q is

$$\frac{\partial^2 LHS}{\partial Q^2} = -Q^{-\beta_1\gamma_1-2}(-\beta_1\gamma_1)\left[(1+\beta_1\gamma_1)+(1-\beta_1\gamma_1)\rho Q/\bar{q}\right].$$

If $0 \leq -\beta_1\gamma_1 \leq 1$, then $\partial^2 LHS/\partial Q^2 \leq 0$ for all $Q \geq 0$. In this case, LHS is a hump-shaped curve in Q.

If $-\beta_1\gamma_1 > 1$, then $\frac{\partial^2 LHS}{\partial Q^2} > 0$ when $Q < \tilde{Q}$ and $\frac{\partial^2 LHS}{\partial Q^2} < 0$ when $Q > \tilde{Q}$, with $\tilde{Q} \equiv \frac{-(1+\beta_1\gamma_1)\bar{q}}{(1-\beta_1\gamma_1)\rho} < \hat{Q}$.

The minimal size of charging network that leads to positive EV adoption in the steady state is given by $\bar{\theta}v(\underline{N}) = P$. So, $\underline{N} = P^{-\beta_2/\beta_1}e^{-\xi/\beta_1}$. The installed base at this threshold is $\underline{Q} = \frac{(1-\delta)C}{\pi(\underline{N})} = \frac{(1-\delta)C}{(P^{\beta_2}e^{\xi})^{1/\beta_1\gamma_1}e^{\eta/\gamma_1}}$. Moreover, $LHS(\underline{Q})>0$ and $\lim_{Q\to+\infty} LHS = -\infty$.

The following cases emerge:

Case (I): If $RHS>LHS_{max}$, RHS and LHS have no intersection point. In this case, $Q^* = 0$ is the only equilibrium.

Case (II): If $LHS(\underline{Q}) < RHS \leq LHS_{max}$, RHS and LHS have two positive intersection points, denoted as Q_S and Q_H, with $Q_S \leq \hat{Q}$ and $Q_H \geq \hat{Q}$. In this case, the origin, Q_S and Q_H are the equilibria.

Case (III): If $RHS \leq LHS(\underline{Q})$, RHS and LHS have one positive intersection point, denoted Q_G. In this case, the origin and Q_G are the equilibria.

The critical mass problem only exists when $LHS(\underline{Q}) < RHS \leq LHS_{max}$. Hence, there exist two price cutoffs, P_{min} and P_{max}, where P_{min} is the solution of

$$(1-\rho\underline{Q}/\bar{q})\underline{Q}^{-\beta_1\gamma_1} = P^{\beta_2}C^{\beta_1\gamma_2}(1-\delta)^{\beta_1\gamma_2}e^{\xi+\beta_1\eta}$$

and

$P_{max} = (1-\beta_1\gamma_1)^{-(1-\beta_1\gamma_1)/\beta_2}(-\beta_1\gamma_1\bar{q}/\rho)^{-\beta_1\gamma_1/\beta_2}C^{-\beta_1\gamma_2/\beta_2}(1-\delta)^{-\beta_1\gamma_2/\beta_2}e^{-(\xi+\beta_1\eta)/\beta_2}$. The critical mass condition is $P_{min} < P \leq P_{max}$.

Next, we derive the stability condition. Any equilibrium Q^* is locally stable if $\left|\frac{\partial Q_t}{\partial Q_{t-1}}\right| < 1$ at $Q_{t-1} = Q^*$ and locally unstable if $\left|\frac{\partial Q_t}{\partial Q_{t-1}}\right| > 1$ at $Q_{t-1} = Q^*$. Consider a small increase $\triangle q$ from such a point. The increase in equilibrium that would be induced by indirect network effects would be $\triangle Q = \left|\frac{\partial Q_t}{\partial Q_{t-1}}\right| \times \triangle q$. This condition says that local network effects must be weak enough so that $\triangle Q < \triangle q$. Conversely, strong local network effects lead to saddle-point instability.

The diffusion dynamics of the EV installed base are given by

$$Q_t = \left[1 - G\left(\frac{P_t - \delta P_{t+1}}{v(N_t)}\right)\right]\bar{q} + (1-\rho)Q_{t-1}.$$

Taking the derivative with respect to Q_{t-1} yields

$$\frac{\partial Q_t}{\partial Q_{t-1}} = -G'(\cdot)\frac{P_t - \delta P_{t+1}}{v^2(N_t)}v'(\cdot)\pi^{-1\prime}(\cdot)\frac{C_t - \delta C_{t+1}}{Q_t^2}\bar{q}\frac{\partial Q_t}{\partial Q_{t-1}} + (1-\rho).$$

With the functional-form assumptions, the above derivative becomes

$$\frac{\partial Q_t}{\partial Q_{t-1}} = \frac{1-\rho}{1 + G'(\cdot)\frac{P_t - \delta P_{t+1}}{v^2(N_t)}v'(\cdot)\pi^{-1\prime}(\cdot)\frac{C_t - \delta C_{t+1}}{Q_t^2}\bar{q}}.$$

$$\frac{\partial Q_t}{\partial Q_{t-1}} = \frac{1-\rho}{1 + \beta_1\gamma_1(\bar{q} - q_t)/Q_t}.$$

In the steady-state, $q_t = \rho Q_t$. So,

$$\frac{\partial Q_t}{\partial Q_{t-1}} = frac1 - \rho 1 + \beta_1\gamma_1(\bar{q} - \rho Q_t)/Q_t.$$

Hence, $\frac{\partial Q_t}{\partial Q_{t-1}} > 1$ when $Q < \hat{Q}$ and $\frac{\partial Q_t}{\partial Q_{t-1}} < 1$ when $Q > \hat{Q}$.

Therefore, any equilibrium Q^* less than $\hat{Q}$ is locally unstable and any Q^* greater than $\hat{Q}$ is locally stable.

Proof of Proposition 2

Taking the derivative of both sides of equation (10) with respect to P yields

$$-\frac{\partial Q}{\partial P}Q^{-\beta_1\gamma_1}\rho/\bar{q} - \beta_1\gamma_1(1-\rho Q/\bar{q})Q^{-\beta_1\gamma_1-1}\frac{\partial Q}{\partial P} = \beta_2 P^{\beta_2-1}C^{\beta_1\gamma_2}(1-\delta)^{\beta_1\gamma_2+\beta_2}e^{\xi+\beta_1\eta}.$$

So,

$$\frac{\partial Q}{\partial P} = \frac{Q^{1+\beta_1\gamma_1}\beta_2 P^{\beta_2-1}C^{\beta_1\gamma_2}(1-\delta)^{\beta_1\gamma_2+\beta_2}e^{\xi+\beta_1\eta}}{(1-\beta_1\gamma_1)\rho Q/\bar{q}+\beta_1\gamma_1}.$$

Hence, $\frac{\partial Q}{\partial P}>0$ when $Q<\hat{Q}$ and $\frac{\partial Q}{\partial P}<0$ when $Q>\hat{Q}$. Because $Q_S<\hat{Q}$ and $Q_H>\hat{Q}$, $\frac{\partial Q_S}{\partial P}>0$ and $\frac{\partial Q_H}{\partial P}<0$.

Similarly, we can get $\frac{\partial Q_S}{\partial \bar{q}}<0$ and $\frac{\partial Q_H}{\partial \bar{q}}>0$, $\frac{\partial Q_S}{\partial \alpha}<0$ and $\frac{\partial Q_H}{\partial \alpha}>0$, $\frac{\partial Q_S}{\partial \bar{\theta}}<0$ and $\frac{\partial Q_H}{\partial \bar{\theta}}>0$, $\frac{\partial Q_S}{\partial \eta}<0$ and $\frac{\partial Q_H}{\partial \eta}>0$.

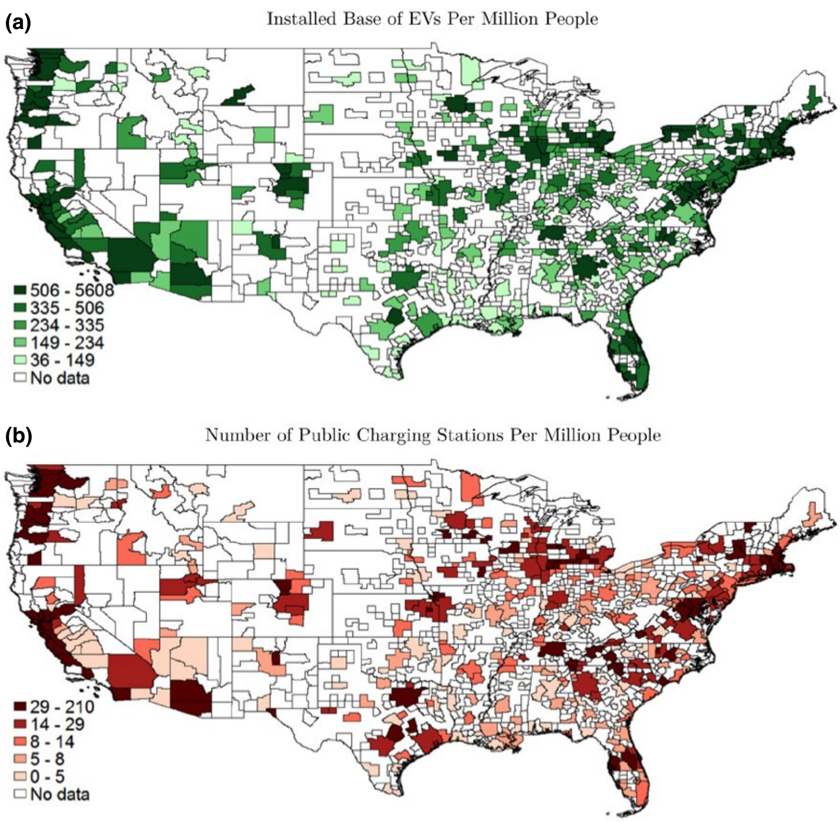

Figure B.1
Spatial Distribution of EV's and Public Charging Stations
[Colour figure can be viewed at *wileyonlinelibrary.com*]

APPENDIX B

Additional Tables and Figures

TABLE B.I

FIRST-STAGE RESULTS OF THE NESTED LOGIT MODEL

	(I): $ln(N_{mt})$		(II): $ln(p_{jmt})$		(III): $ln(s_{jmt\|EV})$	
ln(grocery stores$_m$)* ln(stations$_{t-1}$)	0.168***	(0.019)	0.000	(0.001)	−0.007	(0.011)
$CAFE_{ft-1} - \overline{MPG}_{ft-1}$	−0.003	(0.006)	−0.082***	(0.002)	0.137***	(0.018)
s_{jm0}*$ln(q_{jt})$	−0.011	(0.017)	0.029***	(0.003)	0.196***	(0.055)
ln(gasoline price)*BEV	0.052	(0.116)	0.116***	(0.012)	−0.458**	(0.219)
ln(gasoline price)*PHEV	0.111	(0.112)	−0.064***	(0.009)	−0.110	(0.177)
ln(residential charging from EV project)	−0.010	(0.034)	0.004	(0.001)	0.020	(0.017)
HOV exemption for EVs	−0.054	(0.075)	−0.001	(0.002)	−0.145***	(0.051)
ln(household income)	−0.109	(0.932)	0.022	(0.081)	1.853***	(0.697)
Model-MSA FE		Y		Y	Y	
Year-Quarter FE	Y		Y		Y	
R^2		0.674	0.547		0.412	
Joint F-statistic of IVs	54.76		299.92		272.11	
Observations		13,239		13,239	13,239	

Notes: ln(grocery stores$_m$)*ln(stations$_{t-1}$) is the interaction between log(number of grocery stores at the end of 2012) and log(total number of charging stations in last quarter across all MSA's), $CAFE_{ft-1} - \overline{MPG}_{ft-1}$ is the difference between an automaker's CAFE target and its actual fuel economy last year, s_{jm0} is the market share of the automaker that offers model j in MSA m before the introduction of EV's (from 2007 to 2010), and q_{jt} is the national sales of EV model j in quarter t. Clustered standard errors at the MSA level are in parentheses.

$^{*}p$<0.10, $^{**}p$<0.05, $^{***}p$<0.01.

TABLE B.II
TOP TEN MSAs OF STEADY-STATE EV ADOPTION

Total Adoption		Adoption Per Million	Population
New York, NY	194,637	San Francisco, CA	24,565
San Francisco, CA	105,628	Ann Arbor, MI	23,226
Atlanta, GA	88,625	San Jose, CA	20,444
Miami, FL	61,718	Santa Rosa, CA	18,615
Detroit, MI	60,749	Olympia, WA	17,298
Seattle, WA	55,326	Oxnard, CA	17,038
Boston, MA	55,309	Atlanta, GA	16,722
San Diego, CA	51,511	San Diego, CA	16,617
San Jose, CA	36,800	Seattle, WA	16,272
Sacramento, CA	32,572	Sacramento, CA	15,743
All MSAs	1,140,633	All MSAs	4,709

TABLE B.III
POLICY IMPACTS ON EV ADOPTION BY TYPE

	Steady-State EV Stock		Cost per Induced EVs ($)	
	BEV	PHEV	BEV	PHEV
Fixed-Unit-Subsidy				
$2,500	10,187	10,512	57,057	63,904
$5,000	70,702	70,849	9,521	10,949
$7,500	102,500	102,751	7,683	9,219
$10,000	186,912	187,127	4,614	5,630
$15,000	295,544	295,845	3,096	3,870
Fixed-Duration-Subsidy				
One Year	272,174	346,617	95	151
Three Years	300,395	325,535	636	1,208
Five Years	325,655	300,704	1,251	2,546

Note: The simulations are based on the estimation results of the fourth column of Table IV in the paper.

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