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**Dynamics of Technology Adoption and Critical Mass:
The Case of U.S. Electric Vehicle Market**

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Dynamics of Technology Adoption and Critical Mass: The Case of U.S. Electric Vehicle Market

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Abstract

We examine the dynamics of technology adoption and critical mass in network industries with an application to the U.S. electric vehicle (EVs) market. This market exhibits indirect network effects in that consumer EV adoption and investor deployment of public charging stations are interdependent. In markets with positive indirect network effects, multiple equilibria with different level of technology adoption may exist. The diffusion and ultimately the success of technology depend on the equilibrium structure and property. Under certain market conditions, the issue of critical mass arises and the market needs to pass this critical mass in order to reach the high-adoption equilibrium. Using a data set of quarterly EV sales in 354 U.S. metro areas from 2011 to 2013, we quantify indirect network effects and simulate long-run market outcomes in each of the MSAs. Our analysis provides robust and significant evidence of indirect network effects in this market. Simulations show several different market equilibrium outcomes across the 354 MSAs in the long run with a significant number of them exhibiting multiple equilibria and critical mass. Policy suggestions are provided in order to push these markets to pass the critical mass and move towards the high-adoption equilibrium.

Keywords: electric vehicles, indirect network effects, critical mass
JEL classification: Q4, Q5, R4

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1. Introduction

In many new technology markets, the benefit from adopting the primary good depends on the availability of the complementary goods and the profitability of complementary goods depends on the installed base of primary good users. The interdependence between the demand for the primary good and the supply of the complementary goods is defined as indirect network effects. Examples include computer hardware and software, CD players and titles, video consoles and games, and credit cards. The diffusion of this type of technologies has been the subject of a rich literature dating back to early theoretical studies by Rohlfs (1974), Katz and Shapiro (1985, 1986) and Farrell and Saloner (1985).

In markets with positive indirect network effects, one side of the market tends to wait for the other side to act before taking its own action. Previous literature (Caillaud and Jullien 2003) has emphasized the multiple equilibria issue and the “chicken-and-egg” coordination problem. Theory also tells us that those markets are generally facing a critical mass constraint: short of passing this constraint during the launch stage could spell the ultimate failure of the technology.¹ Our paper examines the issue of critical mass in the context of plug-in electric vehicles (EVs), an important emerging technology that has the potential to transform the transportation sector. Understanding what determines the existence and the size of the critical mass point and exploring how to address this issue have important practical and policy implications.

The electrification of the transportation sector through the diffusion of plug-in electric vehicles (EVs), coupled with cleaner electricity generation, is considered a promising pathway to reduce air pollution from on-road vehicles and to strengthen energy security. The U.S. transportation sector contributes to nearly 30% of U.S. total greenhouse gas emissions, over half of carbon monoxide and nitrogen oxides emissions, and about a quarter of hydrocarbons emissions in recent years. It also accounts for about three-quarters of U.S. petroleum consumption. Different from conventional gasoline vehicles with internal combustion engine, plug-in electric vehicles (EVs) use electricity stored in rechargeable batteries to power the motor and the electricity comes from external power

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¹ See Oren and Smith (1981), Economides and Himmelberg (1995), Fath and Sarvary (2003), and Evans and Schmalensee (2010).

sources. When operated in all-electric mode, EVs consume no gasoline and produce zero tailpipe emissions. But emissions shift from on-road vehicles to electricity generation, which uses domestic fuel source. The environmental benefit critically depends on the fuel source of electricity generation.

Since the introduction of the mass-market models into the U.S. in late 2010, monthly sales of EVs have increased from 345 in December 2010 to 11,286 in December 2014.² Despite the rapid growth, the market share of electric cars is still small: the total EV sales only made up 0.73% of the new vehicle market in 2014. In the 2011 State of the Union address, President Obama set up a goal of having one million EVs on the road by 2015. Based on the market penetration so far, the goal is likely to be met only halfway.³

As a new technology, EVs face several significant barriers to wider adoption including the high purchase cost, limited driving range, the lack of charging infrastructure and long charging time. Although EV owners can charge their vehicles overnight at home, given the limited driving range, consumers may still worry about running out of electricity before reaching their destination. This issue of range anxiety could lead to reluctance to adopt EVs especially when public charging stations are scarce. At the same time, private investors have less incentive to build charging stations if the size of the EV fleet and the market potential are small. The inter-dependence between the EV adoption and the public charging station deployment can be characterized as indirect network effects: the benefit of participation to one side of the market increases in the participation of the other side. If the indirect network effect is strong enough, this new market may be able to grow rapidly because one side attracts the other side. However, multiple equilibria may exist; and in this scenario, failure to pass the initial critical mass point may also set the market to the downward death spiral. Therefore, it is crucial for policy makers to understand how the two sides interact with each other and how to achieve the high-adoption equilibrium.

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² From 1996 to 1998, GM introduced over 1000 first-generation EVs (EV1) in California, mostly made available through leases. In 2003, GM crushed their EVs upon the expiration of the leases.

³ Similar national goals exist in many other countries: Chinese government set up a goal of half a million EVs on the road by 2015 and five million by 2020. German government developed an initiative to reach one million EVs by 2020.

The main objective of this study is to shed some light on the dynamics of technology adoption in the EV market by characterizing the market equilibrium and examining the importance of critical mass in the long-run growth of the market and its policy implications. These are important issues especially given the significant promise the EV technology holds in reducing air pollution and oil usage. However, the diffusion and the long-run survivability of the technology are not well understood from economic perspective. Policy makers in the U.S. and other countries are employing a variety of policies and putting significant resources to promote the EV technology. How much the government support should be and for how long critically hinge on some important aspects of the market including indirect network effects, the properties of market equilibrium, and the issue of critical mass constraint.

We first develop a stylized theoretical model to examine the properties of the dynamic system of EV adoption and charging station investment. The model incorporates indirect network effects on both sides of the market. Our analysis shows: (i) that multiple equilibria may exist; (ii) that the equilibrium properties depend on the nature of indirect network effects, consumer preference and the profitability of public charging stations; (iii) that no one adopts EV in equilibrium if the EV price or the building cost is too high; (iv) that the critical mass exists if the price is within a certain range; and (v) that if the critical mass exists, the EV adoption level at critical mass increases and the EV adoption level at high-adoption equilibrium decreases as the EV price increases or the charging station building cost increases. In one scenario, three equilibria exist with the EV adoption level characterized being low-adoption, middle-adoption and high-adoption. The low-adoption and high-adoption equilibria are locally stable, whereas the middle-adoption equilibrium is unstable. This gives rise to the importance of the critical mass constraint: if the market fails to pass the initial constraint, the market could revert to the low-adoption equilibrium and result in the failure of the technology adoption.

To bring the model to the data, we parameterize our theoretical model and derive a simultaneous system of two log-linear (in parameters) equations: an EV adoption equation that quantifies the effect of the availability of public charging stations on EV diffusion; and an equation on charging station investment that quantifies the effect of the EV fleet installed base on the deployment of charging stations. Recognizing the

endogeneity issue due to simultaneity in both equations, we employ Newey's two-step estimation procedure that can handle random-effect Tobit model with endogenous explanatory variables. We estimate the simultaneous system using a rich data set of quarterly new EV sales by car model and the number of public charging stations in 354 Metropolitan Statistical Areas (MSAs) from 2011 to 2013. Across various specifications, our analysis finds statistically and economically significant indirect network effects on both sides of the market.

With the parameter estimates, we first simulate the EV adoption levels in the long-run equilibrium for all 354 MSAs. We find that 12 of them have no positive equilibrium, 307 of them have one positive equilibrium which is stable, and 35 of them have two positive equilibria where the lower one is unstable and the higher one is locally stable. The average EV ownership per million people in the long-run equilibrium is 7492, compared to 409 in the 3rd quarter of 2013, implying a nearly 18-fold increase.

Furthermore, we simulate the long-run demand curves for three selected MSAs of varying size. Our quantitative results confirm the theoretical predictions. First, when the EV price is above a threshold, for example \$18,893 for a small market and \$40,395 for a medium market, there will be no EV adoption in the long run. Second, when the EV price is below a threshold, for example \$14,024 for a small market and \$22,274 for a medium market, critical mass does not exist, in other words, only one positive equilibrium adoption level exists and it is globally stable. Third, when the EV price is between the two thresholds, two positive equilibria exist where the lower one is the critical mass point. In this case, the critical mass is increasing in price and high-adoption equilibrium is decreasing in price. That is, the higher the EV price, the more difficult to pass the critical mass and the lower the high-adoption level.

To examine the impact of the federal income tax credit of \$7500, we simulate the long-run equilibria for all MSAs under a permanent subsidy program and we predict that the EV ownership would increase by 8% in the long-run equilibrium. Furthermore, we quantify the minimal subsidy as well the duration of the subsidy needed in order for those 35 MSAs with critical mass can avoid this issue. The subsidy size and subsidy duration vary dramatically across markets, depending on the underlying consumer preferences and

investors profitability. The subsidy size ranges from \$1,000 to \$19,100 per car and the subsidy duration ranges from 3 quarters to 84 quarters. The significant variation of the results across geographical markets is driven by the heterogeneity of local demand and supply conditions.

This study directly contributes to the following three strands of literature. First, our study fits into the rich literature on technology adoption in markets with indirect network effects. Previous theoretical work on indirect network effects includes Rohlfs (1974), Katz and Shapiro (1985, 1986), Farrell and Saloner (1985), and many others. More and more empirical studies in the field of industrial organization have emerged in the past two decades, mainly focusing on the markets that can be characterized by classic software and hardware paradigm including the market of CD titles and CD players by Gandal, Kende and Rob (2000), the PDA and compatible software system by Nair, Chintagunta, and Dude (2003), the yellow page market by Rysman (2004), the electronic payment system by Gowrisankaran and Stavins (2004) and Akerberg and Gowrisankara (2006), the radio industry by Berry and Waldfogel (1999), and the video game industry by Clements and Ohashi (2005), Corts and Lederman (2009), Lee (2013), and Zhou (2014).

Second, our study also contributes to the literature on critical mass issue in network industries. Most previous studies derive theoretical or conceptual explanations of why some markets display critical mass phenomena. Markus (1987) shows the underlying production function and consumer heterogeneity lead to critical mass in media markets. Cabral (1990, 2006) 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) studies the critical mass issue in two-sided markets. They conceptually show that this hurdle depends on the nature of network effects, the dynamics of customer behavior, and the distribution of customer tastes. Very few empirical studies exist. The only one that we are aware of is Grajek and Kretschmer (2012) who identifies the critical mass in the global cellular telephone market using a country-level quarterly data on the cellular telephone market in the early stages of the first digital generation (2G). They found that cellular telephone would have “taken off” without any installed base at an average price of 36 US cents per minutes in pioneering markets and that the critical mass is reached at 38 US

cents when the installed base is about 24% of the population. Our paper differs from theirs in several aspects. First, EV market that we are studying is a market with indirect network effect, whereas their market, cellular telephone market, is a market with direct network effect. Hence, both of our modeling and empirical specification are different from theirs. Second, our data set covers 17 models in 354 markets during 12 quarters. With such rich variations across geographical markets and over time, we can better identify the network effects using instrumental variables after car model, market and quarter fixed effects. Third, EV market is an important emerging technology that has the potential to transform the transportation sector due to its environmental benefits and energy security. Because of that, many countries put a significant amount of resources and subsidies in this market. So, our study has important policy implications.

Third, our study adds to the emerging literature on the electric vehicle market. Congressional Budget Office (2012) estimates the effect of income tax credits for EV buyers based on previous research on the effects of similar tax credits on traditional hybrid vehicles. DeShazo, Sheldon, and Carson (2014) use a state-wide survey of new car buyers in California to estimate price elasticities and willingness to pay for different vehicles and then simulate the effect of different rebate designs. Using market-level sales data during 2011-2013, our previous work, Li et al. (2005) offer a first study in quantifying the role of indirect network effects in the market and their implications on government subsidies. In the study, we find statistically and economic significant indirect network effects on both sides of the market: a 10% increase in the number of charging station would increase EV sales by 8% while a 10% increase in EV stock would increase charging stations by about 6%. Policy simulations suggest that subsidizing charging stations is three times as effective as subsidizing EV purchase (the current policy). This result is driven by: (1) stronger indirect network effects from charging stations to EV demand relative to the other side of the market; and (2) low consumer sensitivity to EV price (price elasticity of -1.27).

Section 2 presents a stylized model to show the dynamics of the system. Section 3 briefly describes the EV market and the data. Section 4 presents the empirical strategy and the estimation results. Section 5 quantifies the critical mass point and Section 6

examines the policy impacts. Section 7 concludes. Appendix provides the proofs of all propositions.

2. A Stylized Theoretical Model

In this section, we build a stylized model to show how the nature of indirect network effects, consumer preference for public charging stations, and EV public charging station investors' profitability affect the dynamics of the system.

Let Q_t and N_t denote the installed base of a representative EV model and the number of public charging stations at time t , respectively. Denote P_t as the price of an EV and C_t as the building cost of a public charging station. In each time period, given the installed base of EVs and public charging stations in the last period, Q_{t-1} and N_{t-1} , consumers decide whether to adopt EVs and investors decide whether to build public charging stations; and these two groups of agents make their decisions simultaneously.

We do not model the strategies of car manufactures or policy makers because our focus is to identify the conditions for the critical mass phenomena and, if so, to quantify the critical mass. Given our analysis, car manufacturers or policy makers can implement appropriate strategies to help the market to pass the critical mass and move to the high-adoption equilibrium. To achieve this goal, we only need to analyze the consumers' adoption behavior and investors' entry behavior. Econometrically, we do not impose any structure on car manufactures' or policy makers' behavior, and we will use instrumental variable techniques to address the endogeneity problem.

2.1 EV Purchase

There are $\bar{q}$ potential new consumers in each period. A potential buyer i 's indirect utility from adopting an EV in period t is

$$-P_t + \theta_i[v(N_t^e) + \delta v(N_{t+1}^e) + \dots]$$

where θ_i is i 's idiosyncratic preference for public charging station relative to EV price, N_t^e is the expected number of public charging stations at time t , δ is discount factor, and $v(\cdot)$ is the flow utility from vehicle service. We assume that v is an increasing function

and $v(0) = 0$. We also assume θ_i follows a distribution with a smooth density function $g(\cdot)$ and c.d.f $G(\cdot)$ on the interval $[\theta, \bar{\theta}]$.

If she adopts an EV in period $t + 1$, her utility discounted at period t is

$$-\delta P_{t+1}^e + \theta_i [\delta v(N_{t+1}^e) + \delta^2 v(N_{t+2}^e) + \dots].$$

Let $\hat{\theta}_t$ be the consumer who is indifferent between adopting it in period t and adopting it in in period $t + 1$. It is given by

$$\hat{\theta}_t = \frac{P_t - \delta P_{t+1}^e}{v(N_t^e)}.$$

Here, $P_t - \delta P_{t+1}^e$ corresponds to $-\lambda(t)$ in Economides and Himmelberg (1995). The first term P_t measures the cost of buying the EV today and the second term δP_{t+1}^e measures the cost of waiting one period. So, $P_t - \delta P_{t+1}^e$ represents the relative cost of buying today rather than tomorrow.

Then, we can get the new sales of EVs in period t as a function of the number of public charging stations:

$$q_t = \left[1 - G\left(\frac{P_t - \delta P_{t+1}^e}{v(N_t^e)}\right) \right] \bar{q}. \quad (1)$$

Notice that because $v(0) = 0$, we have $q_t = 0$ if $N_t^e = 0$, That is, no one adopts EV if the expected installed base of public charging stations is zero.

Suppose the depreciate rate of EV is ρ , with $\rho < 1$. Then, we get the installed base of EVs in period t

$$Q_t = q_t + (1 - \rho)Q_{t-1}.$$

Or,

$$Q_t = \left[1 - G\left(\frac{P_t - \delta P_{t+1}^e}{v(N_t^e)}\right) \right] \bar{q} + (1 - \rho)Q_{t-1}. \quad (2)$$

2.2 Public Charging Station

Within a period, each EV driver's demand for public charging station j is denoted by $D_j(p_1, \dots, p_N)$ where N is the number of stations available in that period and p_j is the

price charged by station j . We assume that charging station's marginal cost is constant, denoted by c . Then, the per-consumer profit is $\pi_j = (p_j - c)D_j(p_1, \dots, p_N)$. We assume that demand is symmetric and the profit function is quasi-concave in p_j .⁴ Given this assumption, there exists an equilibrium in which all stations charge the same price, denoted as p . The equilibrium price would depend on the number of stations in the market, $p(N)$. As a result, we can write the per-consumer profit for each station as a function of the number of public charging stations:

$$\pi(N) = (p(N) - c)D(p(N), \dots, p(N)).$$

Denote Q_t^e as the expected installed base of EVs at time t . If an investor builds a station in period t , its expected profit is

$$-C_t + Q_t^e \pi(N_t) + \delta Q_{t+1}^e \pi(N_{t+1}^e) + \dots$$

If the investor builds a station in period $t + 1$, its expected profit discounted in period t is

$$-\delta C_{t+1}^e + \delta Q_{t+1}^e \pi(N_{t+1}^e) + \delta^2 Q_{t+2}^e \pi(N_{t+2}^e) + \dots$$

In a free-entry equilibrium, investors are indifferent between building in period t and building in period $t + 1$. Then, we can get the number of charging stations as a function of the installed base of EVs:

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

where $C_t - \delta C_{t+1}^e$ represents the relative cost of entering today rather than tomorrow. Clearly, $N_t = 0$ if $Q_t^e = 0$, that is, no investor enters if the expected installed base of EVs is zero.

2.3 Steady State

Equation (2) and (3) are the two side-response functions, where equation (2) characterizes consumers' response to charging station side whereas equation (3) characterizes charging station investors' response to consumer adoption.

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⁴ This assumption is consistent with the properties of most commonly adopted competition models.

We assume $P_t = P$ and $C_t = C$ in steady state. The fulfilled expectations equilibrium is a pair of path of the installed bases of EVs and public charging stations $\{Q_t, N_t\}$ such that expectations are fulfilled and the installed bases are stable, i.e., it fulfills:

- (i) EV adoption: equation (2)
- (ii) Public charging station: equation (3)
- (iii) Fulfilled expectation of the installed base of public charging stations: $N_t = N_t^e$
- (iv) Fulfilled expectation of the installed base of EVs: $Q_t = Q_t^e$
- (v) Steady state condition: $Q_t = Q_{t-1}$ and $N_t = N_{t-1}$

Hence, the steady state installed bases (Q^*, N^*) are the solutions to the following two equations:

$$Q^*(N^*) = q^*/\rho = [1 - G((1 - \delta)P)/v(N^*)]\bar{q}/\rho. \quad (4)$$

$$N^*(Q^*) = \pi^{-1}((1 - \delta)C/Q^*). \quad (5)$$

Substituting (3) into (2) gives the dynamic adjustment of the EV installed base:

$$Q_t = \left[1 - G\left(\frac{P_t - \delta P_{t+1}}{v\left\{\pi^{-1}\left(\frac{C_t - \delta C_{t+1}}{Q_t}\right)\right\}}\right)\right] \bar{q} + (1 - \rho)Q_{t-1}. \quad (6)$$

From Equation (6), we can write Q_t as a function of Q_{t-1} , denoted as $Q_t = \psi(Q_{t-1})$, where the shape of $\psi(\cdot)$ depends on those of $v(\cdot)$, $\pi(\cdot)$, $G(\cdot)$ and the values of P and C .

Proposition 1: *There always exists a degenerated equilibrium where no consumer adopts EV and no investor builds public charging stations, that is, $Q_t^* = 0$ and $N_t^* = 0$ for all t . This is the classical “no-chicken-no-egg” outcome.*

Depending on the shapes of $v(\cdot)$, $\pi(\cdot)$, and $G(\cdot)$, and values of P and C , we have the following four cases in general.

Case I:

Figure 3 illustrates the first case. Figure 3 (a) plots the two side-response functions given by equation (4) and (5). $N^*(Q)$ and $Q^*(N)$ interacts only at the origin so the origin is the only equilibrium. In this case, there are too few potential EV buyers with high values of θ_i ; as a result, no one adopts this technology no matter how it is started. Figure

3 (b) shows the adjustment of EV installed base, $Q_t = \psi(Q_{t-1})$ given by equation (6). We can see that the origin is a globally stable equilibrium.

Case II:

Figure 4 illustrates the second case. In this case, $N^*(Q)$ and $Q^*(N)$ are tangent at a point E with positive EV adoption. The origin and the point E are the two equilibria. The origin is stable and the point E is unstable.

Case III:

Figure 5 illustrates the third case. In this case, $N^*(Q)$ and $Q^*(N)$ intersects at the origin and two points with positive EV adoption, denoted as point S and point H. The low-adoption equilibrium (origin O) and the high-adoption equilibrium (point H) are locally stable, whereas the middle-adoption equilibrium (point S) is a saddle point which is unstable. If there are more than three equilibria, theory (see Burdett and Wright 1998) tells us that the locally stable equilibria and saddle-points must alternate.

To get to the high-adoption equilibrium, the EV installed base needs to pass a critical mass level, which is shown by Q_S . Trajectories beginning above this critical trajectory tend to point H, while trajectories beginning below this path will move back to the origin. Hence, we need to reach a point above the critical trajectory in order for positive feedback to drive the market to the high-adoption equilibrium H rather than to the origin.

Case IV:

Figure 6 illustrates the last case. In this case, $N^*(Q)$ and $Q^*(N)$ intersects at the origin and a point G with positive EV adoption. The point G is a globally stable equilibrium. In this scenario, it only takes a small shock such as some initial investment in public charging stations or EV adoption for the system to move toward the stable equilibrium G. This scenario does not entail a critical mass and it is only a matter of time for the system to finally reach the stable equilibrium G.

2.4 A Special Case

To take the model to the data, we make the following functional-form assumptions:

$$(i) \ v(N_t) = (N_t)^{\tilde{\beta}_1}$$

$$(ii) \pi(N_t) = \tilde{\gamma}_0(N_t)^{\tilde{\gamma}_1}$$

(iii) Consumer preference's distribution is $G(\theta) = \theta^\tau/(\bar{\theta})^\tau$ on the interval $[0, \bar{\theta}]$.

Notice that in our empirical analysis in Section 4, we will allow $\tilde{\beta}_1, \tilde{\gamma}_0, \tilde{\gamma}_1, \bar{\theta}$ and τ to vary across markets and over time. That is, the values of those parameters depend on time-varying local demographics and error terms.

Under the assumptions (i) – (iii), equation (1) and (3) generate two simple log-linear equations that is convenient to work with empirically, one equation of EV adoption and one equation of public charging station⁵:

$$\ln((\bar{q} - q_t)/\bar{q}) = \min \{0, \beta_0 + \beta_1 \ln(N_t) + \beta_2 \ln(P_t - \delta P_{t+1})\} \quad (7)$$

$$\ln(N_t) = \max \{0, \gamma_0 + \gamma_1 \ln(Q_t) + \gamma_2 \ln(C_t - \delta C_{t+1})\} \quad (8)$$

where $\beta_0 = -\tau \ln(\bar{\theta})$, $\beta_1 = -\tau \tilde{\beta}_1$, $\beta_2 = \tau$, $\gamma_0 = -\ln(\tilde{\gamma}_0)/\tilde{\gamma}_1$, $\gamma_1 = -1/\tilde{\gamma}_1$ and $\gamma_2 = 1/\tilde{\gamma}_1$.

Here, β_1 and γ_1 capture the magnitude of the indirect network effects on the two sides. Feedback loops arise if both β_1 and γ_1 are non-zero. Intuitively, a shock to the system, for example an increase in demand shifter 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 the shocks (either positive or negative) in either side of the market such as tax credit for EV purchases or subsidy on charging station investment. β_2 (positive) captures consumer's sensitivity to EV price and γ_2 (negative) captures public charging station's investor sensitivity to building cost.

The positive EV adoption levels at equilibrium are given by

$$(1 - \rho Q^*/\bar{q})(Q^*)^{-\beta_1 \gamma_1} = \exp\{\beta_0 + \beta_1[\gamma_0 + \gamma_2 \ln((1 - \delta)C)] + \beta_2 \ln((1 - \delta)P)\}. \quad (9)$$

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⁵ These two equations are similar to Gandal, Kende and Rob (2000) for the CD industry. Their data contains the total sales of CD players and the total sales of CDs over 30 quarters. On the contrary, each observation in our data set is by car model/MSA/year-quarter. Hence, we add car model fixed effect, MSA fixed effect and year-quarter fixed effect to control for the time-invariant product attributes and local conditions and the time-varying national shocks. The inclusion of those rich fixed effects can help us correctly identify the indirect network effects.

Suppose that the parameters have the expected signs, i.e., $\beta_1 < 0, \beta_2 > 0, \gamma_1 > 0, \gamma_2 < 0$. Furthermore, we assume $\beta_1\gamma_1 \in (-1, 0)$ which is confirmed in our empirical analysis. The left-hand side (LHS) is a hump-shaped curve in Q^* and the right-hand side (RHS) is constant in Q^* . Depending on the values of the model parameters, we have the following proposition.

Proposition 2: *There exist two thresholds χ_1 and χ_2 which are functions of the model parameters (i.e., $\beta, \gamma, \rho, \delta$) such that*

- (i) *when $P^{\beta_2}C^{\beta_1\gamma_1} > \chi_2$, $Q^* = 0$ is the only steady state and is globally stable.*
- (ii) *when $P^{\beta_2}C^{\beta_1\gamma_1} = \chi_2$, $Q^* = 0$ and $Q^* = Q_E > 0$ are the two steady states where $Q^* = 0$ is stable and $Q^* = Q_E$ is unstable.*
- (iii) *when $\chi_1 \leq P^{\beta_2}C^{\beta_1\gamma_1} < \chi_2$, $Q^* = 0$, $Q^* = Q_S > 0$ and $Q^* = Q_H > Q_S$ are the three steady states where $Q^* = 0$ and $Q^* = Q_H$ are stable and $Q^* = Q_S$ is unstable. In this scenario, $Q^* = Q_S$ is the critical mass point that is required to pass in order to reach the high-adoption stable steady states $Q^* = Q_H$.*
- (iv) *when $P^{\beta_2}C^{\beta_1\gamma_1}(\bar{q})^{-\beta_1\gamma_1} < \chi_1$, $Q^* = 0$ and $Q^* = Q_G > 0$ are the two steady states where $Q^* = 0$ is unstable and $Q^* = Q_G$ is globally stable.*

The first two cases are the “no-chicken-no-egg” scenarios. Graphically, the above four cases correspond to Figure 2, 3, 4 and 5, respectively. In Figure 2 (c), P and C are high or the market size is small so that the RHS curve is above LHS curve entirely. In this case, the origin O is the only equilibrium which is globally stable. In Figure 3 (c), the RHS curve is tangent to the LHS curve. In this case, the origin O and point E are equilibria where the origin is stable and point E is unstable. In Figure 4 (c), P and C are relatively low or the market size is relatively large so that the RHS curve intersects the LHS curve twice. So, there are three equilibria, the origin O , the point S and the point H . Since point S is on the upward-sloping part of the LHS curve so it is unstable; whereas point H is on the downward-sloping part of the curve so it is locally stable. Hence, the point S is the critical mass point. When the installed base reaches the critical mass, it moves towards the high-adoption equilibrium (point H) without any change of other factors such as lower prices or higher qualities. In Figure 5 (c), P and C are very low or

the market size is very large so that the RHS curve interacts the LHS curve only once but at a high level. In this case, the origin O and point G are equilibria where the origin is unstable and point G is globally stable.

The proposition 2 gives the conditions when the critical mass phenomenon exists. It implies that this phenomenon exists if $\chi_1 \leq P^{\beta_2} C^{\beta_1 \gamma_1} < \chi_2$. Because $\beta_1 < 0$, $\beta_2 > 0$, $\gamma_1 > 0$, $\gamma_2 < 0$, this condition is satisfied when the EV price and the installation cost of stations are low enough. It also states that “no-chicken-no-egg” is the only equilibrium and is globally stable if EV price or the installation cost of charging stations (P and C) are too high or the market size is too small.

From equation (9), we can calculate the long-run demand elasticity with respect to EV price:

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

Two implications are worthy pointed out. First, consider the case (iii) with two positive equilibria. Since $Q_S < \hat{Q} \equiv \frac{-\beta_1 \gamma_1 \bar{q}}{(1 - \beta_1 \gamma_1) \rho}$ and $Q_H > \hat{Q} \equiv \frac{-\beta_1 \gamma_1 \bar{q}}{(1 - \beta_1 \gamma_1) \rho}$, 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 point is increasing in EV price and the high-adoption equilibrium is decreasing in EV price. This results are summarized in the following proposition.

Proposition 3: *The critical pass point Q_S is non-decreasing in P and C and non-increasing in $\bar{q}$. The high-adoption point Q_H is non-increasing in P and C and non-decreasing in $\bar{q}$.*

Second, consider the high-adoption equilibrium, that is, Q_H in case (iii) or Q_G in case (iv). In the case of positive indirect network effects, $\beta_1 < 0$ and $\gamma_1 > 0$. Hence, the magnitude of the elasticity is larger than that of no indirect network effects. In other words, the impact of price on equilibrium EV adoption is scaled up due to the positive indirect

network effects and moreover, this scale factor depends on the magnitude of the indirect network effects.

2.6 Policy Implications

The federal government has adopted several policies to support the EV industry including income tax credits for EV purchase, financial support for vehicle manufacturers and charging infrastructure, and programs for public education about electric vehicles. The tax credits for EV buyers account for about one-fourth of the budgetary cost and are likely to have the greatest impact on vehicle sales.

Based on our analysis above, we can qualitatively predict the impact of the current tax credits policy. Our analysis in section 2.6 implies that the impact of subsidizing EV price on EV adoption depends on the magnitude of indirect network effects, i.e., the value of β_1 and γ_1 . The stronger the snowball effect, the larger the impact of such a subsidy policy on EV adoption.

Furthermore, Figure 7 graphically shows that that reducing EV price would shift the RHS curve down. First, consider a market whose RHS is currently located at RHS_1 so that it does not have any positive equilibrium. A moderate price cut may move its RHS to RHS_3 so that it would have two positive equilibria where the lower one is unstable and the higher one is stable, and a dramatic price cut may move its RHS even further to RHS_4 so that it would have only one positive equilibrium that is locally stable. Now consider a market currently located at RHS_3 . This market has an unstable positive equilibrium Q_S and a locally stable positive equilibrium Q_H . If there is no subsidy, this market can not pass the critical mass point Q_S and hence it can not move to the high-adoption equilibrium Q_H . If a sufficient subsidy on the EV price would push the RHS_3 down to RHS_4 , then this market would only have only one positive equilibrium Q_G that is stable, that is, it avoids the critical mass problem. Lastly consider a market currently located at RHS_4 . A price cut would push RHS_4 down even further and hence increase the level of Q_G .

To sum up, the quantitative impact of the subsidy policy depends on the current locations of LHS curve and RHS curve. In other words, it depends on the current EV price, the current installation cost of public charging stations, and the values of the model

parameters capturing the nature of network effects, the dynamics of consumer behavior and the dynamics of EV charger station investors' behavior, and the distribution of consumer.

In section 6, we will quantify the impacts of the current policy and analyze what government policies (both with respect to subsidy level and the duration of support) need to be imposed to push the markets with critical mass issues to pass the critical mass point and move towards the high-adoption equilibrium.

3. Industry Background and Data

In this section, we first present industry background focusing on the trend of EV sales and the deployment of public charging stations in the U.S. and discuss important barriers to EV adoption. Next we present the data used in the empirical analysis.

3.1 Industry background

Tesla Motors played a significant role in the come-back of electric vehicles by introducing Tesla Roadster, an all-electric sport car in 2006 and beginning general production in March 2008. However, the model has a price tag of over \$120,000, out of the price range for average buyers. A BEV Nissan Leaf (\$28,980) and a PHEV, Chevrolet Volt (\$34,185) were introduced into the U.S. market in December 2010, marking the beginning of the mass market for EVs.

As depicted in Figure 7, quarterly EV sales increased from less than 2,000 in the first quarter of 2011 to nearly 30,000 in the last quarter of 2013. During the same period, the number of public charging stations has increased from about 800 to over 6,000. Nevertheless, the EV market is still very small: EV sales only made up 0.73% (or 118,682) of the total new vehicle sales in the U.S. in 2014 and there are only about 9,000 public charging stations, compared to over 120,000 gasoline stations.

There are several significant barriers to EV adoption. First, EVs are more expensive than their conventional gasoline vehicle counterparts. The manufacturer's suggested retail prices (MSRP) for the 2014 model of Nissan Leaf and Chevrolet Volt are \$28,980 and \$34,185, respectively, while the average price for a comparable conventional vehicle

(e.g., Nissan Sentra, Chevrolet Cruze, Ford Focus and Honda Civic) is between \$16,000 and \$18,000. A major reason behind the cost differential is the cost of battery and as the battery technology improves, the cost should come down. To reduce the price gap between EVs and their gasoline counterparts, the Energy Improvement and Extension Act of 2008, and later the American Clean Energy and Security Act of 2009 grant tax credit for new qualified EVs. The minimum credit is \$2,500 and the credit may be up to \$7,500, based on each vehicle's battery capacity and the gross vehicle weight rating. Moreover, several states have established additional state-level incentives to further promote EV adoption such as tax exemptions and rebates for EVs and non-monetary incentives such as HOV lane access, toll reduction and free parking.⁶

The second notable barrier to EV adoption is the limited driving range. BEVs have a shorter range per charge than conventional vehicles have per tank of gas, contributing to consumer anxiety of running out of electricity before reaching a charging station. Auto manufacturers usually target a range of 100 miles on a fully charged battery. 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. Chevrolet Volt has an all-electric range of 38 miles, beyond which it will operate under gasoline mode. This range is sufficient for daily household vehicle trips but may not be enough for longer distance travels. The diffusion of EVs should benefit from a wider distribution of public-accessible charging infrastructure, which would reduce range anxiety and allow PHEVs to operate more under the all-electric mode to save gasoline.

The third barrier is the long charging time. It takes much longer to charge EVs than to fill up gasoline vehicles. A BEV may not be able to get fully charged overnight if just using a regular 120 Volt electric plug (it takes 21 hours for Nissan LEAF to get fully charged) (source: Hybridcars.com 2014 Nissan Leaf Overview). To get faster charging, BEV drivers either need to install a charging station at home or go to public charging stations. Unlike BEVs, PHEV batteries can be charged not only by an outside electric

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⁶ A study by the Electricity Power Research Institute (EPRI, 2013) estimates the lifetime cost (including upfront purchase cost less incentives, maintenance and operation cost) of EV ownership and finds it is comparable with that of comparable conventional gasoline and hybrid vehicles under reasonable assumptions such as vehicle lifetime vehicle miles of 150,000, gasoline price of \$3.62 and electricity price of 12 cents per kWh and a discount rate of 5%.

power source, but by the internal combustion engine as well. Having the second source of power may alleviate range anxiety but the shorter electric range limits the fuel cost savings from EVs.

There are two types of public charging stations: 240 volt AC charging (Level 2 charging) and 500 volt DC high-current charging (DC fast 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 and only 10-30 minutes at a DC fast charging station. The installation of charging stations involves a variety of costs including charging station hardware, other materials, labor and permit. 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. Charging stations can be found at workplace parking lot, shopping centers, convenience shops, restaurant, dealers and existing gasoline stations. Owners of charging stations are often motivated by a variety of considerations such as boosting their sustainability credentials, attracting customers for their main business, and providing a service for employees. Charging stations are often managed by one of the major national operators such as Blink, ChargePoint, and eVgo.

3.2 Data

We construct a panel dataset consisting of quarterly EV sales by vehicle model and the number of charging stations available at 354 MSAs from 2011 to 2013. Table 1 presents summary statistics of the variables used in our regression analysis.

Data on quarterly vehicle sales of each EV model in each MSA is purchased from IHS Automotive. The sales data include 17 EV models: 10 BEVs and 7 PHEVs. Due to different introduction schedules, there were two vehicle models in our 2011 data: Nissan LEAF and Chevrolet Volt. The 2012 data include four more vehicle models: Ford Focus EV, Mitsubishi i-MiEV, Fisker Karma, and Toyota Prius Plug-in. The 2013 data include 11 additional models: Honda Accord Plug-in, Ford C-Max Energi, Cadillac ELR, Honda Fit EV, Fiat 500E, Smart ForTwo Electric Drive, Tesla Model S, Porsche Panamera, Toyota RAV4, Chevrolet Spark EV, and Ford Transit Connect EV. In 2013, the top four EV models are Nissan Leaf, Chevrolet Volt, Telsa Model S and Toyota Prius plug-in with market shares (sales) of 25.8% (22,610), 24.4% (23,094), 17.4% (18,650) and 9.4%

(12,088), respectively.

We select the 354 MSAs (out of 381 MSAs in total) for which observations are available in all three years, and their EV sales accounted for 83% of the national EV sales during our data period. Panel A of Figure 8 depicts the spatial pattern of EV ownership (the number of EVs per million people) in the last quarter of 2013. It shows that large urban areas have a higher concentration of EVs. The MSA with the highest concentration is San Jose-Sunnyvale-Santa Clara, CA MSA with 5608 EVs per million people by the end of 2013. The next two MSAs are both nearby San Francisco-Oakland-Fremont and Santa Cruz-Watsonville. The MSA with the lowest concentration is Laredo, TX with only 36 EVs per million people (9 EVs with a population of a quarter of a million).

We obtain detailed information on location and open date on all public-accessible charging stations from the Alternative Fuel Data Center (AFDC) of the Department of Energy. By matching the ZIP code of each charging station to an MSA and using the station open date (which was provided in the off-line version of their data base), we coconstruct the total number of public charging stations available in each quarter for each MSA. Panel B of Figure 8 (b) shows the spatial distribution of charging stations (the number of charging stations per million people). The pattern is very similar to what we observe in Panel A for EV ownership. The correlation coefficient between the two variables is 0.63, partly reflecting the interdependence of EVs and charging stations. The top three MSAs with the most charging stations per million people is Corvallis, OR, Olympia, VA and Napa, CA with 210, 170, 117 public charging stations per million people, respectively. These three MSAs are the number 11th, 5th, and 6th in terms of the EV concentration in Panel A.

In addition, we collect data on state-level incentives such as tax credit and rebates for both electric vehicles and public charging stations from AFDC. From the American Chamber of Commerce cost-of-living index database, we collect quarterly gasoline prices for each MSA from 2008 to 2013. In case of missing MSAs in the cost-of-living data, we use the average price of the other cities in the same state. Household demographics are collected from the American Community Survey.

4. Estimation

In this section, we specify our empirical model, describe the estimation strategy and report the estimation results. In specific, we employ Newey's two-step estimation procedure to estimate two equations, an EV adoption equation and a public charging station deployment equation. The two equations are empirical counterparts of equation (7) and (8).

4.1 Estimation Equations

Let j denote EV model such as Nissan Leaf or Tesla Model S, m denote market (i.e., MSA), and t denote year-quarter such as the first quarter of 2012. We estimate the following simultaneous equation system:

$$\ln(1 - s_{jmt}) = \min \{0, \beta_0 + \beta_1 \ln(N_{mt}) + \beta_2 \ln(P_{jmt} - \delta P_{jmt,t+1}) + \beta'_3 X_{jmt}^{EV} + \vartheta_{jmt}\} \quad (10)$$

$$\ln(N_{mt}) = \max \{0, \gamma_0 + \gamma_1 \ln(Q_{mt}) + \gamma_2 \ln(C_{mt} - \delta C_{mt,t+1}) + \gamma'_3 X_{mt}^{CS} + \omega_{mt}\} \quad (11)$$

where equation (10) is the EV adoption equation and equation (11) is the public charging station deployment equation.

In equation (10), $s_{jmt} = q_{jmt}/\bar{q}_{mt}$ is the market share of EV model j in a market m at time t . From American Community Survey, we obtain the total number of households in each MSA. We use the inter-purchase time to new cars (7 years or 28 quarters, see Sudhir 2001 and Albuquerque and Broonenberg 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. Stated formally, the total potential consumers in a market m in quarter t is given by $\bar{q}_{mt} = \#households_{mt}/interpurchase\ time$.

N_{mt} is the total number of public charging stations that have been built in market m by the end of the year-quarter t .⁷ 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

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⁷ We use the number of charging stations instead of the total number of charging outlets to represent the availability of charging infrastructure but the qualitative findings remain if we use the number of charging units.

both federal and state levels). X_{jmt}^{EV} is a vector of other control variables including local gasoline price, home charging subsidy, local personal income, and a full set of MSA-model random effects (e.g., Nissan Leaf in San Francisco) and year-quarter fixed effects (e.g., the first quarter of 2011). In the linear regressions, MSA-model random 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; Kahn and Vaughn 2009) and demand shocks for each model (e.g., a stronger preference or dealer presence for Nissan Leaf in San Francisco). ϑ_{mt} is the unobserved demand shocks that are time-varying and market-specific (for example, unobserved local government subsidy for purchasing EVs or market-specific promotions for a vehicle model that vary over time).

In equation (11), Q_{mt} denotes the installed base of EVs by time t . C_{mt} is the building cost of a public charging station after federal and local tax credits. X_{mt}^{CS} is a vector of other covariates affecting public charging station investors' investment decisions including a dummy variable indicating whether this MSA belongs to the Northeast Electric Vehicle Network (NEVN)⁸, a dummy variable indicating whether there exists public grants or funding to build charging infrastructure, and a full set of MSA random effects and year-quarter fixed effects. The MSA random effects control for time-invariant and MSA-specific preferences for charging stations. For example, some MSAs may be "greener" than others and invest more on alternative fuel infrastructure. Similarly, MSAs with a higher population density and limited private installment of charging stations may have more public charging stations. The year-quarter fixed effects control for time-varying common shocks to charging station investment across MSAs such as macro-economic conditions. The error term ω_{mt} captures the unobserved shock to charging station investment, for instance, the unobserved local policies to support the charging station building.

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⁸ NEVN was launched in late 2011 after near one million grant was announced in September 2011 by Department of Energy. It is one of 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 through the region and work together to attract additional public and private investment in infrastructure for clean vehicles. Participating NEVN would lower the cost of installing public charging stations.

4.2 Random Tobit with Endogenous Explanatory Variables

Let the model be:

$$y_{mt} = \max \{0, X_{mt}\beta + \alpha h_{mt} + \mu_m + \epsilon_{mt}\} \quad (12)$$

$$h_{mt} = Z_{mt}\varphi + \lambda_m + \vartheta_{mt} \quad (13)$$

where $\mu_m \sim N(0, \sigma_\mu^2)$, $\lambda_m \sim N(0, \sigma_\lambda^2)$, $\epsilon_{mt} \sim N(0, \sigma_\epsilon^2)$ and $\vartheta_{mt} \sim N(0, \sigma_\vartheta^2)$. Moreover, ϵ_{mt} and ϑ_{mt} are independent of Z_{mt} . What we want to estimate are β , α , σ_μ^2 and σ_ϵ^2 .

If $\text{corr}(\epsilon_{mt}, \vartheta_{mt}) \neq 0$, then h_{mt} is correlated with the error term ϵ_{mt} . In this case, we have the endogeneity problem. Note that ϵ_{mt} and ϑ_{mt} are jointly normally distributed, we can write

$$\epsilon_{mt} = \rho \vartheta_{mt} + e_{mt},$$

where $\rho = \text{corr}(\epsilon_{mt}, \vartheta_{mt})$ and $e_{mt} \sim N(0, \sigma_e^2)$ independent of ϑ_{mt} . Since both ϵ_{mt} and ϑ_{mt} are independent of Z_{mt} , then so is e_{mt} .

Insert this expression for ϵ_{mt} into the regression (12)

$$y_{mt} = \max \{0, X_{mt}\beta + \alpha h_{mt} + \rho \vartheta_{mt} + \mu_m + e_{mt}\} \quad (14)$$

Notice that e_{mt} is independent of h_{mt} . We employ Newey's two-step estimation procedure (see Newey (1987)). In the first step, we estimate the equation (13) using random-effect model. Then, we can obtain the residual $\hat{\vartheta}_{mt}$. In the second step, we estimate the equation (14) using random-effect Tobit, with replacement of ϑ_{mt} with $\hat{\vartheta}_{mt}$.

4.3 Instrumental Variables

This section discusses the instrument variables that we will use to estimate equations (10) and (11). We focus on the identification of two coefficients capturing interdependence between EV adoption and charging station deployment, β_1 and γ_1 .

4.3.1 EV Adoption Equation

It is well documented in the vehicle demand literature that failing to control for unobserved product attributes could lead to downward bias in the price coefficient estimates (for example Berry et al. (1995); Beresteanu and Li (2011)). Using MSA-model

random effects to control for unobserved product attributes alleviates the need to use the methodology developed in Berry et al. (1995) to deal with price endogeneity where they only have national-level sales data (i.e., one market).⁹ The price coefficient β_2 is identified from the fact that effective EV prices vary across markets and over time due to state-level subsidies and temporal price variations. The state-level subsidies do not vary over time but they could be still endogenous in the sense that state governments may set subsidies in response to (time-invariant) unobserved demand shocks. Our linear regressions include MSA effects to control for these (time-invariant) state-level unobserved demand shocks.

Although we include a rich set of control variables, the charging station variable $\ln(N_{mt})$ is still endogenous due to simultaneity: the unobserved time-varying and market-specific demand shocks ϑ_{jmt} could be correlated with the unobserved shock to charging station investment ω_{mt} and thus correlated with $\ln(N_{mt})$. We address this problem with instrumental variables. The instrument that we use is the interaction term between the number of grocery stores and supermarkets in a MSA in 2012 with the number of the charging stations in all MSAs (lagged for one quarter). Grocery stores and supermarkets are a major owners of public charging stations and they build the to attract customers and boost green credentials among other reasons. These places could be good sites for public charging stations because EV drivers can charge their vehicles while. Nissan has been actively partnering with grocery store owners to build public charging stations. Kroger, the country's largest grocery store owner, has partnered with ECOtality Inc. to install about 300 charging stations in their store locations across the country. Our data shows that the number of grocery stores in an MSA is positively correlated with the number of charging stations.

However, the number of grocery stores does not vary with time in our sample period and it is therefore absorbed by the MSA effects. To introduce temporal variation, we multiply it with the lagged number of existing charging stations in all MSAs, which captures the national-level trend in charging station investments due to aggregate shocks

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⁹ The methodology in Berry et al. (1995) uses a contracting mapping technique to first back out product-level fixed effects (mean utility) in the first stage and then uses IV strategy to estimate the remaining preference parameters based on the assumption that observed product attributes are not correlated with unobserved product attributes, which could be a strong assumption (Klier and Linn 2012).

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 for the IV is that national shocks to charging station investment (captured by the lagged number of charging station in all MSAs) have disproportional effects on charging station investment in different MSAs: those MSAs with a larger number of grocery stores and supermarkets (hence better endowment of good sites for charging stations) will be affected by these national shocks more than others, leading to variations in charging stations across MSAs. Our first-stage results in Table 4 to be discussed below show that the interaction term has a positive and highly statistically significant impact on charging station investments.

We argue that this instrument should satisfy the exogeneity assumption. The number of grocery stores and supermarkets is unlikely to affect EV sales directly. There might be common unobservables that influence both the EV sales and the number of grocery stores, especially at the cross-sectional level. However, our model controls for MSA effects and should capture the time-invariant unobservables. At the temporal dimension, EV sales vary a lot from year to year but the number of grocery stores is very stable given that it is a very mature industry. In fact, the number of grocery stores is measured at the end of 2012. The temporal variation in the IV comes from the total (lagged) number of charging stations in all MSAs. Year-quarter fixed effect would control for time-varying shocks that are common across MSAs.

Our IV strategy leverages the interaction term between a national-level variable with only temporal variation and a MSA-level variable with only spatial variation. The rationale behind the IV is that different MSAs have different pre-existing conditions/ability to absorb national shocks to charging station investment such as changes in macro-economic conditions and costs.

4.3.2 Charging Station Equation

The issue of endogeneity due to simultaneity also arises in equation (11): the error term ω_{mt} could be correlated with ϑ_{jmt} and thus correlated with $\ln(Q_{mt})$. To address this issue, we use a set of current and past gasoline prices as instrumental variables. The fuel cost savings from driving EVs depend on the price difference between gasoline and

electricity, which varies across locations. In MSAs with higher gasoline prices, consumers may have a stronger incentive to purchase EVs. Because the installed base of EVs is the cumulative sales of EVs, we include gasoline prices in the current quarter as well as annual gasoline prices in the past three years as instruments. For example, for the installed base of EVs in the 2nd quarter in 2013, we use the gasoline price in the 2nd quarter in 2013, the average gasoline price in 2012, the average gasoline price in 2011, and the average gasoline price in 2010 as instrumental variables.

Gasoline prices should affect the installed base of EVs, which is also confirmed in the first-stage regressions in Table 5. But they are unlikely to affect public 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 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. The net benefit of building charging stations depends on the EV market potential (proxied by the installed base of EVs) 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. There is no direct link between electricity and gasoline prices (after controlling for common shocks such as national economic conditions using time fixed effects).

4.4 Baseline Estimation Results

Table 2 reports the estimation results for the EV adoption equation. The first column reports the OLS estimation results, the second column reports the 2SLS estimation results, the third column reports the Tobit estimation result and the last column reports the Tobit with IV estimation results. All regressions provide negative and statistically significant impacts of the availability of public charging stations, ranging from -0.00031 to -0.00007. Notice that our dependent variable is the log of residual market share. Hence, negative sign indicates positive indirect network effect, that is, more public charging stations

attract more EV adoption. All regressions provide positive and statistically significant coefficients on the purchase price change. This implies negative effect from price on EV adoption. The impact of gasoline price on the residual EV adoption is negative, implying that people are more likely to adopt EVs if the gasoline price increases. The coefficient before the residential charging facilities from EV project is negative but insignificant, implying that people are more likely to adopt EVs if EV project provides more residential charging facilities. The coefficients before the income are negative and statistically significant, implying that high-income people are more likely to adopt EVs than low-income people.

Table 3 reports the OLS, IV, Tobit and Tobit with IV estimation results of the charging station equation. All regressions provide positive and statistically significant coefficients before the EV adoptions, ranging from 0.272 to 0.733. Positive sign indicates positive indirect network effect, that is, more EV drivers attract more public charging station investors. The coefficient before 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 northeast network is positive and significant, implying that investors are more likely to invest in the areas that are members of the northeast network. As we discussed before, this is because this network would reduce the investment cost. All specifications provide positive and statistically significant impacts of government subsidies on public charging station installation.

4.5 Alternative Specifications for EV Adoption Equation

In the baseline specification for the EV adoption equation, the dependent variable is $\ln(1 - s_{jmt})$, which makes the parameter estimates hard to interpret. We re-estimate the EV adoption equation by using $\ln(q_{jmt})$ as the dependent variable. We replace the log of the change of EV prices $\ln(P_{jmt} - \delta P_{jmt+1})$ with the log of the EV price $\ln(P_{jmt})$. The estimation results are reported in Table 6. Across all specifications, the installed base of public charging stations has significant positive effect on the EV adoption; the effect of EV price is negative and significant; and the effect of gasoline price is positive and significant.

In order to account for the competition among EV models, we follow the literature, for example, Berry and Waldfogel (1999) and Rysman (2004), and estimate a nested logit model specified as

$$\begin{aligned} \ln(s_{jmt}) - \ln(s_{0mt}) = & \beta_0 + \beta_1 \ln(N_{mt}) + \beta_2 \ln(P_{jmt}) \\ & + \tau \ln(s_{jmt|EV}) + \beta_3' X_{jmt}^{EV} + \vartheta_{jmt}, \end{aligned} \quad (10)$$

where s_{jmt} is the market share of model j in m in quarter t , $s_{jmt|EV}$ is the share of people who choose a car model j given that they choose to buy an EV. Parameter τ measures the correlation in unobserved (to the econometrician) utility from different EV models. As the parameter τ goes to one, correlation within the category goes to one, implying that EV models become identical. When τ is zero, we return to the logit model and EV models give completely idiosyncratic utility.

The estimation results are reported in Table 7. Again, the coefficient on $\ln(N_{mt})$ is positive and statically significant for all specifications. The significant of the public charging station parameter suggests that the present of positive feedback is robust to alternative specifications of the EV adoption equation.

5. Equilibrium Characterizations

In this section we use simulations to characterize the equilibria of each of 354 markets based on equations (10) and (11) and the estimates from our baseline model (column 4 in table 2 and column 4 in table 3). An important caveat of the our analysis is to assume the market conditions in both the supply and demand sides (such as the number of EV models, EV prices and household income etc.) are fixed as in the third quarter of 2013 except that the stock of EVs and charging stations evolves over time. We also remove the current subsidy in the simulation, amounting to the assumption that the subsidy had expired after the 3rd quarter of 2013. Our goal here is to understand the equilibrium properties under a given (i.e. the 3rd quarter in 2013) market conditions.

5.1 Equilibrium

We compute the EV adoption levels in the long-run equilibrium for all 354 MSAs in the sample. Panel (a) in Figure 10 depicts the number of positive and stable equilibria for

the 354 MSAs. Among these MSAs, 12 of them (3%) have no positive equilibrium; 307 of them (87%) have one positive equilibrium which is locally stable; and 35 of them (10%) have two positive equilibria where the lower one is unstable and the higher one is locally stable, implying the existence of the critical mass.

Panel (b) shows the installed base of EVs per million people in the long-run equilibrium (the highest equilibrium point in case of multiple equilibria). The average EV stock per million people in the long-run equilibrium is 7492, compared to 409 in the 3rd quarter of 2013, implying a nearly 18-fold increase. The range of EV stocks in the long-run equilibrium is from 0 to 89,667, compared to the range of 36 to 5608 in the 3rd quarter of 2013. It is interesting to note that 12 MSAs will revert to zero EVs in the long-run equilibrium with the market condition observed in 2013.

The total EV stock across these MSAs in the long-run equilibrium is 2.77 million units, a dramatic increase from the 116,448 units by the third quarter of 2013.¹⁰ Although it would be a nearly 25-fold increase in terms of EV ownership, the share of EVs among the total vehicle stock would only be about one point. This small share critically depends on the market conditions observed in the 3rd quarter of 2013. As more EV models are slated to come on the market and the EV prices continue to drop, the EV stocks in the long-run equilibrium are likely to be larger than what our simulations predict. Nevertheless, our results suggest that the penetration of the EV technology faces significant challenges forward.

5.2 Long-Run Demand Curves

To further understand how the market conditions, in particular EV prices, affects the existence of critical mass, we focus on three MSAs of varying size: Albany, GA, Augusta-Richmond County, GA-SC, and San Francisco-Oakland-Fremont, CA. In these three MSAs, the installed base of EVs in 2013 was at about the 10th, 50th and 90th percentiles, respectively. Figure 11 shows how the EV stock in the long-run equilibria is affected by EV prices for the three markets (the total panel for Albany and the bottom panel for San Francisco). The left graph shows how the critical mass level (Q_S) varies

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¹⁰ Among all the 354 MSAs, 295 of them (83%) have fewer than 300 units, 33 of them (9%) have between 300 to 1000 units, and 26 of them (7%) have more than 1000 units in the long-run equilibrium.

with EV prices and the right graph shows how the high-adoption level (Q_G) varies with EV prices.

Consistent with our qualitative analysis in Section 2, we have the following three findings. First, when the EV price is higher than a threshold, for example \$18,893 for a small market and \$40,395 for a medium market, there will be no EV adoption in the long run. Second, when the EV price is below a threshold, for example \$14,024 for a small market and \$22,274 for a medium market, critical mass does not exist, in other words, only one positive equilibrium adoption level exists and it is globally stable. Third, when the EV price is between the two thresholds, two positive equilibria exist where the lower one is the critical mass point. In this case, the critical mass is increasing in the EV price and high-adoption equilibrium is decreasing in the EV price. That is, the higher the EV price, the more difficult to pass the critical mass and the lower the high-adoption level.

5.3 Role of Indirect Network Effects

We examine the impacts of indirect network effects on the long-run equilibrium by simulate market outcomes under varying degree of indirect network effects from charging station availability to EV adoption while holding everything else the same. We consider four scenarios of indirect network effects in equation 10: $\beta_1 = 0$, $\beta_1 = 0.5\hat{\beta}_1$ (half of estimated value), $\beta_1 = \hat{\beta}_1$ (estimated value), and $\beta_1 = 2\hat{\beta}_1$ (double of estimated value). Figure 12 shows the total EV adoption of all 354 MSAs in the sample on the equilibrium paths for the four scenarios. The larger the β_1 , the larger the EV stock is in equilibrium and the longer it takes to reach the equilibrium. This is consistent with the predictions of our theoretical analysis in section 2.6.

6. Policy Simulations

Our stylized theoretical model described in section 2 suggests that the impact of government subsidy policies depends on the strength of the indirect networks, consumer preferences, investors' profitability from building public charging stations, the EV price and charging station building cost. In the previous two sections, we have empirically recovered those factors for each MSA using a panel data covering 354 MSAs and 8

quarters, and furthermore, we have shown that the equilibrium outcomes vary dramatically across markets due to the heterogeneity of local conditions. In this section, we examine the policy impact of the current federal income tax credit policy for EV buyers. Furthermore, we simulate the minimal subsidy size and subsidy duration for each MSA with critical mass to avoid this issue.

6.1 Impact of Income Tax Credits

The federal government has adopted several policies to support the EV industry 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 those policies will be about \$7.5 billion through 2017. The tax credits for EV buyers account for about one-fourth of the budgetary cost and are likely to have the greatest impact on vehicle sales. Under the tax credits policy, EVs purchased in or after 2010 are eligible for a federal income tax credit up to \$7,500. Most popular EV models on the market are eligible for the full amount. The credit will expire once 200,000 qualified EVs have been sold by each manufacturer.

We have discussed the qualitative impact of a permanent price cut in Section 2.6. To quantify the impact of the federal income tax credit of \$7500, we simulate the long-run equilibria for all MSAs under a permanent subsidy program. Compared with the outcomes in the no-subsidy scenario, the number of MSAs with zero positive equilibrium would reduce from 12 to 6 of them and the number of MSAs with two positive equilibria would reduce from 35 to 21. The total EV stock across all MSAs in the long-run equilibrium would increase by about 8% from 2.77 million to 2.99 million.

6.2 Subsidy Policy to Surpass the Critical Mass

For the 35 MSAs that have more than one positive equilibrium, we simulate the minimal subsidy as well as the duration of the subsidy (the number of quarters) needed in order for the long-run equilibrium does not suffer from the issue of critical mass. Since the price variable enters only on the RHS in equation (9), we change the level of subsidy (hence price) so that only one positive equilibrium will emerge. Graphically, this is

equivalent to move down the RHS line in panel (c) of Figure 5 so that it only has one interaction with the LHS line. The second column in Table 8 provides the minimal subsidy needed for the 35 MSAs. These required subsidy amounts vary dramatically across markets. It ranges from \$1,000 in Winston-Salem, NC and \$19,100 in Charleston, WV. Our theoretical analysis suggests that this variation is driven by the heterogeneity of the local demand and supply conditions, see the discussion in Section 2.6 for more details.

Our theoretical analysis in Section 2 also suggests that as long as a market achieves an EV stock higher than the critical mass point (i.e., the Q_S in panel (c) of Figure 5), the market will converge to the locally stable high-adoption equilibrium (i.e., Q_H in panel (c) of Figure 5). Therefore, we further calculate the minimal duration of subsidy that are needed for each market to pass its critical mass point given its minimal subsidy amount. The results are reported in the third column of Table 8. The duration ranges from 3 quarters in Dallas-Fort Worth-Arlington, TX and 84 quarters in Sumter, SC.

7. Conclusion

Electric vehicles as a new technology hold the potential to fundamentally change the transportation sector. The diffusion of EVs coupled with cleaner electricity generation such as renewables can provide a promising pathway to dramatically reduce air pollution from on-road vehicles and to strengthen energy security. Similar to many other new technologies studies, the EV market exhibits indirect network effects which have important implications on market outcomes. In this paper, we aim to quantify indirect network effects and to understand the issue of critical mass in the EV market.

We first analyze a stylized theoretical model of a dynamic system of EV adoption and charging station investment with indirect network effects to examine the equilibrium properties of the system and the impacts of indirect network effects. Our analysis shows that the equilibrium outcomes depend on the nature of indirect network effects, consumer preference, EV prices, and the profitability of public charging stations. As the EV price increases or the charging station building cost increases, the EV adoption level at critical mass increases and the EV adoption level at high-adoption equilibrium decreases. In the long run, a variety of equilibrium outcomes could emerge and one of market outcomes

exhibit multiple positive equilibria and the critical mass. If either consumer adoption or investor participation is below the critical mass, the system would converge to the low-adoption equilibrium where there is no EV and no public charging station.

Using detailed vehicle sales and charging station data by quarter from 2011 to 2013 in 354 MSA in the U.S., our empirical analysis finds economically significant indirect network effects on both sides of the market across a variety of model specifications. Based on model parameter estimates, our simulations under the prevailing market conditions observed in the 3rd quarter of 2013 show several different market equilibrium outcomes across the 354 MSAs in the long run with 35 of them exhibiting multiple equilibria and critical mass. Our simulations suggest that significant government subsidy (e.g., over \$5000) is needed to push most of these 35 MSAs to pass the critical mass and move towards the high-adoption equilibrium. The total EV stock across the MSAs in the long-run equilibrium would only amount to about one percent of the vehicle stock, suggesting the market conditions (e.g., supply and demand factor) need to be significantly improved in order to see wide consumer adoption of the EV technology in the long run.

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Table 1: Data Summary Statistics

Variables	Mean	Std. Dev.
<i>Panel (a): vehicle demand equation by market</i>		
Ln (residual demand)	9.90	0.04
Ln (No. of charging stations)	1.26	1.25
Ln (EV purchase tax incentives)	8.31	1.71
Ln (gasoline prices)	1.25	0.08
Number of observations	4228	
<i>Panel (b): vehicle demand equation by product</i>		
Ln (residual demand)	8.51	0.04
Ln (retail price-tax incentives)	3.38	0.41
Ln (dollar per mile)	-3.17	0.24
Ln (gasoline prices)	1.25	0.07
Number of observations	16260	
<i>Panel (c): Charging station equation</i>		
Ln (No. of charging stations)	1.26	1.25
Ln (No. of EV installed base)	2.76	1.91
Northeast network	0.11	0.31
Tax credit for charging station (%)	3.19	12.42
Public funding or grants	0.22	0.42
Number of observations	4228	

Table 2: EV Purchase Equation with the $\ln(1 - s_{jmt})$ as the Dependent Variable

	(1) OLS	(2) IV	(3) Tobit	(4) Tobit IV
$\ln(N_{mt})$	-0.00017*** (0.00003)	-0.00031*** (0.00009)	-0.00009*** (0.00002)	-0.00007*** (0.00002)
$\ln(P_{jmt} - \delta P_{jm,t+1})$	0.00021*** (0.00003)	0.00021*** (0.00003)	0.00022*** (0.00004)	0.00022*** (0.00004)
$\ln(\text{gasoline price})$	-0.00046* (0.00028)	-0.00044 (0.00028)	-0.00123*** (0.00035)	-0.00105*** (0.00035)
$\ln(\text{residential charging from EV project})$	-0.00004 (0.00003)	-0.00004 (0.00003)	-0.00002 (0.00002)	-0.00002 (0.00002)
$\ln(\text{personal income})$	-0.00477** (0.00229)	-0.00446** (0.00226)	-0.00122*** (0.00022)	-0.00165*** (0.00022)
σ_u			0.00158*** (0.00003)	0.00156*** (0.00003)
σ_e			0.00124*** (0.00001)	0.00124*** (0.00001)
ρ_{ue}				-0.00013*** (0.00002)
Model-MSA	FE	FE	RE	RE
Year-Quarter	FE	FE	FE	FE
Observations	13,452	13,413	13,452	13,413

Note: The IV in columns (2) is the interaction between the number of grocery stores and the total number of stations in all MSAs. Clustered standard errors at the MSA level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Charging Station Equation with $\ln(N_{mt})$ as the Dependent Variable

	(1) OLS	(2) IV	(3) Tobit	(4) Tobit IV
$\ln(Q_{mt})$	0.320*** (0.026)	0.666*** (0.184)	0.272*** (0.020)	0.733*** (0.098)
$\ln(C_{mt} - \delta C_{m,t+1})$	-0.007 (0.007)	-0.010 (0.008)	-0.016 (0.015)	-0.014 (0.015)
Northeast Network	0.292** (0.123)	0.190 (0.129)	0.690*** (0.065)	0.537*** (0.073)
Public Funding	-0.077* (0.042)	-0.054 (0.045)	-0.087** (0.034)	-0.062* (0.034)
σ_u			1.896*** (0.102)	1.912*** (0.103)
σ_e			0.389*** (0.007)	0.387*** (0.007)
ρ_{ue}				-0.475** (0.099)
MSA	FE	FE	RE	RE
Year-quarter	FE	FE	FE	FE
Observations	3874	3874	3874	3874

Note: The dependent variable is $\ln(N_{mt})$. The instrument variable in columns (3) and (4) is the gasoline price (current and past years). Clustered standard errors at the MSA level are in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: First Stage Results for EV Purchase Equation

	$\ln(N_{mt})$
Grocery*Stations	0.225*** (0.017)
$\ln(P_{jmt} - \delta P_{jmt,t+1})$	-0.002 (0.011)
$\ln(\text{gasoline price})$	0.213* (0.126)
$\ln(\text{residential charging from EV project})$	-0.009 (0.010)
$\ln(\text{personal income})$	1.758 (1.130)
R ²	0.704
Observations	13413

Note: The model includes year-quarter fixed effects and MSA fixed effects. Clustered standard errors at the MSA level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: First Stage Results for Charging Station Equation

Variables	$\ln(Q_{mt})$
Northeast Network	0.216** (0.108)
$\ln(\text{Charging Station Installation Cost})$	0.006 (0.009)
Public Funding	-0.088* (0.053)
$\ln(\text{Current Gasoline Price})$	0.649** (0.293)
$\ln(\text{Gasoline Price Last Year})$	4.261** (1.205)
$\ln(\text{Gasoline Price Two Years Ago})$	2.322*** (0.908)
$\ln(\text{Gasoline Price Three Years Ago})$	3.903*** (1.202)
R ²	0.908

Notes: The number of observations is 3874. The model includes year-quarter fixed effects and MSA fixed effects. Standard errors are clustered at MSA level. *Significant at 10%, **significant at 5%, ***significant at 1%.

Table 6: EV Purchase Equation with $\ln(q_{jmt})$ as the Dependent Variable

	(1) OLS	(2) IV	(3) Tobit	(4) Tobit IV
$\ln(N_{mt})$	0.354*** (0.029)	0.918*** (0.076)	0.434*** (0.022)	0.494*** (0.023)
$\ln(\text{retail price} - \text{tax incentives})$	-1.419*** (0.137)	-1.285*** (0.128)	-0.808*** (0.078)	-0.814*** (0.078)
$\ln(\text{gasoline price})$	0.327** (0.166)	0.199 (0.190)	0.599* (0.323)	0.853** (0.323)
$\ln(\text{residential charging from EV project})$	0.016 (0.012)	0.023** (0.011)	0.010 (0.017)	0.006 (0.017)
$\ln(\text{personal income})$	1.140** (0.764)	-0.012 (0.921)	1.659*** (0.228)	0.875** (0.241)
σ_u			1.705*** (0.034)	1.698*** (0.034)
σ_e			0.984*** (0.010)	0.979*** (0.010)
ρ_{ue}				-0.219*** (0.023)
Model-MSA	FE	FE	RE	RE
Year-Quarter	FE	FE	FE	FE
Observations	16220	16172	16220	16172

Note: The dependent variable is $\ln(q_{jmt})$. The IV in columns (2) and (4) is the interaction between the number of grocery stores and the total number of stations. Clustered standard errors at the MSA level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: EV Purchase Equation with $\ln(s_{jmt})$ as the Dependent Variable

	(1) OLS	(2) IV
$\ln(N_{mt})$	0.374*** (0.034)	0.918*** (0.075)
$\ln(\text{retail price} - \text{tax incentives})$	-0.561*** (0.097)	-0.419*** (0.088)
$\ln(s_{jmt EV})$	0.703*** (0.017)	0.709*** (0.017)
$\ln(\text{gasoline price})$	0.590*** (0.212)	0.475*** (0.228)
$\ln(\text{residential charging from EV project})$	0.008 (0.012)	0.008 (0.012)
$\ln(\text{personal income})$	-0.096 (0.873)	-0.096 (0.873)
Model-MSA FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	16220	16172

Note: The dependent variable is $\ln(s_{jmt}) - \ln(s_{0mt})$. The IV in columns (2) is the interaction between the number of grocery stores and the total number of stations. Clustered standard errors at the MSA level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Subsidy Needed to Avoid Critical Mass in 35 MSAs

MSA	Subsidy Size (\$ per car)	Duration (Quarters)
ALTOONA, PA	5,200	63
AMARILLO, TX	2,600	21
AUGUSTA-RICHMOND COUNTY, GA-SC	12,700	12
BATON ROUGE, LA	10,200	14
BEAUMONT-PORT ARTHUR, TX	13,100	17
BIRMINGHAM-HOOVER, AL	7,400	9
CANTON-MASSILLON, OH	2,300	12
CHARLESTON, WV	19,100	35
CHATTANOOGA, TN-GA	5,200	11
COEUR D'ALENE, ID	6,000	58
CUMBERLAND, MD-WV	1,000	68
DALLAS-FORT WORTH-ARLINGTON, TX	1,800	3
DOTHAN, AL	1,500	44
FARGO, ND-MN	8,600	32
HICKORY-LENOIR-MORGANTON, NC	6,500	13
HOUSTON-SUGAR LAND-BAYTOWN, TX	12,700	4
HUNTSVILLE, AL	6,400	19
LEWISTON-AUBURN, ME	10,100	68
MADERA-CHOWCHILLA, CA	2,800	17
MCALLEN-EDINBURG-MISSION, TX	12,800	14
MEMPHIS, TN-MS-AR	12,600	9
MOBILE, AL	9,800	21
MONROE, LA	2,600	31
MORRISTOWN, TN	6,100	61
NEW ORLEANS-METAIRIE-KENNER, LA	16,000	10
PARKERSBURG-MARIETTA-VIENNA, WV-OH	1,000	12
PITTSBURGH, PA	2,500	9
RICHMOND, VA	10,000	9
SAN ANTONIO-NEW BRAUNFELS, TX	11,700	10
SCRANTON--WILKES-BARRE, PA	3,800	10
SUMTER, SC	4,800	84
VIRGINIA BEACH-NORFOLK-NEWPORT NEWS, VA-NC	11,500	9
WICHITA FALLS, TX	6,700	54
WINSTON-SALEM, NC	1,000	3
YOUNGSTOWN-WARREN-BOARDMAN, OH-PA	14,500	9

Figure 1: Monthly Sales of Electric Vehicles in the U.S.

Figure 2: Global Outlook of Light-duty Vehicle Sales by Technology Type

https://www.iea.org/publications/freepublications/publication/EV_PHEV_Roadmap.pdf

Figure 3: Long-Run Equilibrium (Case I)

Figure 4: Long-Run Equilibrium (Case II)

Figure 5: Long-Run Equilibrium (Case III)

Figure 6: Long-Run Equilibrium (Case IV)

(a) Two Side-Response Curves

(b) Dynamics of EV Adoption

(c) Equilibrium EV Adoption

Figure 7: Policy Impacts of EV Purchase Subsidy

Figure 8: U.S. National EV sales and public charging stations

Note: the quarterly EV sales plotted include both BEV and PHEV sales. Data source: Hybridcars.com monthly sales dashboard and Alternative Fuel Data Center of the Department of Energy

Figure 9: Spatial distributions of EVs and public charging stations

Panel (a) Installed base of EVs per million people

Panel (b) Public charging stations per million people

Note: map boundaries define metropolitan statistical areas. Data source: HIS Automotive and DOE Alternative Fuel Data Center (4th quarter of 2013)

Figure 10: Spatial Distribution of EVs in the Long-Run Equilibrium

Panel (a): Number of Positive Equilibria in the long-run

Panel (b): Installed Based of EVs in the Long-run Equilibrium

Note: The simulation of long-run equilibrium is based on the market condition in 2013. The simulated EV stock in the long-run equilibrium in Panel (b) is the level in the high equilibrium point in case of multiple equilibria.

Figure 11: EV Prices and Long-Run EV Stock

Note: The top panel is for Albany, GA, and second panel is for Augusta-Richmond County, GA-SC, and the third panel is for San Francisco-Oakland-Fremont, CA. The left graph shows how the critical mass level (Q_S) varies with EV prices and the right graph shows how the high-adoption level (Q_G) varies with EV prices.

Figure 12: EV Adoption Path with Varying Degree of Indirect Network Effects

Note: Each curve depicts the EV stock over time under a given value of β_1 (the effect of charging station availability on EV adoption)

Appendix:

Proof of Proposition 1:

On the one hand, suppose consumers' belief $N_t^e = 0$. Because $v(0) = 0$ and $G(\infty) = 1$, $q_t = 0$ from equation (1). Hence, the installed base $Q_t = 0$.

On the other hand, suppose investors' belief $Q_t^e = 0$. No investor will enter, that is, $N_t = 0$.

Therefore, $Q_t^* = 0$ and $N_t^* = 0$ for all t is a fulfilled equilibrium.

Proof of Proposition 2:

First, we show the conditions for the existence of critical mass points.

The RHS of equation (9) is constant in Q . The partial derivative of the LHS of the equation (9) with respect to Q is

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

The maximum point $\hat{Q} = \frac{-\beta_1 \gamma_1 \bar{q}}{(1 - \beta_1 \gamma_1) \rho}$.

The second derivative of LHS with respect to Q is

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

So, when $-\beta_1 \gamma_1 \in (0, 1)$, $\frac{\partial^2 LHS}{\partial^2 Q} < 0$. Thus, LHS is a hump-shaped curve in Q . That is,

LHS is increasing in Q when $Q < \hat{Q}$ and decreasing in Q when $Q > \hat{Q}$.

LHS achieves maximum point at $Q = \hat{Q}$ and notice that $\hat{Q}$ is positive because $\beta_1 < 0$ and $\gamma_1 > 0$.

$$LHS_{max} = (1 - \beta_1 \gamma_1)^{\beta_1 \gamma_1 - 1} (-\beta_1 \gamma_1 \bar{q} / \rho)^{-\beta_1 \gamma_1}.$$

Moreover, $\lim_{Q \rightarrow 0} LHS = 1$ and $\lim_{Q \rightarrow +\infty} LHS = 0$.

Hence, we have the following four cases.

- (i) If $RHS > LHS_{max}$, RHS and LHS have no intersection point, and thus $Q^* = 0$ is the only equilibrium.
- (ii) If $RHS = LHS_{max}$, RHS and LHS have one positive intersection point, denoted as Q_E . So, both 0 and Q_E are equilibria.

- (iii) If $LHS_{max} > RHS \geq 1$, RHS and LHS have two positive intersection point, denoted as Q_S and Q_H , with $Q_S < \hat{Q}$ and $Q_H > \hat{Q}$. So, there are three equilibria, 0, Q_S and Q_H .
- (iv) If $0 < RHS < 1$, RHS and LHS have one positive intersection point, denoted as Q_G . So, there are two equilibria, 0 and Q_G .

The critical mass problem only exists in the case (iii).

The condition of $RHS = 1$ is $\beta_0 + \beta_1[\gamma_0 + \gamma_2 \ln((1 - \delta)C)] + \beta_2 \ln((1 - \delta)P) = 0$.

$$\text{That is } C^{\beta_1 \gamma_2} P^{\beta_2} = (1 - \delta)^{-(\beta_1 \gamma_2 + \beta_2)} e^{-\beta_0 - \beta_1 \gamma_0} \triangleq \chi_1.$$

The condition of $LHS_{max} = RHS$ is

$$C^{\beta_1 \gamma_2} P^{\beta_2} = (1 - \delta)^{-(\beta_1 \gamma_2 + \beta_2)} e^{-\beta_0 - \beta_1 \gamma_0} (1 - \beta_1 \gamma_1)^{\beta_1 \gamma_1 - 1} (-\beta_1 \gamma_1 \rho / \bar{q})^{-\beta_1 \gamma_1} \triangleq \chi_2$$

Hence, the existence condition of critical mass is $\chi_1 \leq C^{\beta_1 \gamma_2} P^{\beta_2} < \chi_2$.

Next, we show the stability condition.

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

The diffusion dynamics of the EV installed base is 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 derivative with respect to Q_{t-1} yields

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

So, we have

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

With the functional form assumptions, the above derivative becomes

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

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

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

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

Proof of Proposition 3:

For simplicity, let M denote the RHS of equation (9). Taking derivative of both sides with respect to M we get

$$-\rho \frac{\partial Q}{\partial M} Q^{-\beta_1\gamma_1} - \beta_1\gamma_1 (\bar{q} - \rho Q) Q^{-\beta_1\gamma_1-1} \frac{\partial Q}{\partial M} = 1$$

So,

$$\frac{\partial Q}{\partial M} = \frac{-Q^{1+\beta_1\gamma_1}}{(1 - \beta_1\gamma_1)\rho Q + \beta_1\gamma_1\bar{q}}$$

So, $\frac{\partial Q}{\partial M} > 0$ iff $Q < \hat{Q}$ and $\frac{\partial Q}{\partial M} < 0$ iff $Q > \hat{Q}$.

Since $Q_S < \hat{Q}$ and $Q_G > \hat{Q}$, we have $\frac{\partial Q_S}{\partial M} > 0$ and $\frac{\partial Q_G}{\partial M} < 0$.

Because $\frac{\partial M}{\partial P} > 0$ and $\frac{\partial M}{\partial C} > 0$, then $\frac{\partial Q_S}{\partial P} > 0$, $\frac{\partial Q_S}{\partial C} > 0$, $\frac{\partial Q_G}{\partial P} < 0$, and $\frac{\partial Q_G}{\partial C} < 0$.

Taking derivative of both sides of equation (9) with respect to $\bar{q}$, we get

$$\left(1 - \frac{\rho}{\bar{q}} \frac{\partial Q}{\partial \bar{q}} + \frac{\rho Q}{\bar{q}^2}\right) Q^{-\beta_1\gamma_1} - \beta_1\gamma_1 (1 - \rho Q/\bar{q}) Q^{-\beta_1\gamma_1-1} \frac{\partial Q}{\partial \bar{q}} = 0$$

So,

$$\frac{\partial Q}{\partial \bar{q}} = \frac{Q\bar{q} + \rho Q^2/\bar{q}}{(1 - \beta_1\gamma_1)\rho Q + \beta_1\gamma_1\bar{q}}$$

So, $\partial Q/\partial \bar{q} < 0$ iff $Q < \hat{Q}$ and $\partial Q/\partial \bar{q} > 0$ iff $Q > \hat{Q}$.

Since $Q_S < \hat{Q}$ and $Q_G > \hat{Q}$, we have $\partial Q_S/\partial \bar{q} < 0$ and $\partial Q_G/\partial \bar{q} > 0$.