The Market for Electric Vehicles: Indirect Network Effects and Policy Design

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Abstract: The market for plug-in electric vehicles (EVs) exhibits indirect network effects due to the interdependence between EV adoption and charging station investment. Through a stylized model, we demonstrate that indirect network effects on both sides of the market lead to feedback loops that could alter the diffusion process of the new technology. Based on quarterly EV sales and charging station deployment in 353 metro areas from 2011 to 2013, our empirical analysis finds indirect network effects on both sides of the market, with those on the EV demand side being stronger. The federal income tax credit of up to $7,500 for EV buyers contributed to about 40% of EV sales during 2011–13, with feedback loops explaining 40% of that increase. A policy of equal-sized spending but subsidizing charging station deployment could have been more than twice as effective in promoting EV adoption.

JEL Codes: L62, Q48, Q58

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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

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energy security. The US transportation sector contributes to nearly 30% of US 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 US petroleum consumption. Different from conventional gasoline vehicles with internal combustion engines, plug-in electric vehicles (EVs) use electricity stored in rechargeable batteries to power the motor, and the electricity comes from external power 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 a domestic fuel source. The environmental benefit critically depends on the fuel source of electricity generation.[1]

Since the introduction of the mass-market models into the United States in late 2010, monthly sales of EVs have increased from 345 in December 2010 to 13,388 in December 2015.[2] Despite the rapid growth, the market share of electric cars is still small: the total EV sales only made up 0.82% of the new vehicle market in 2015. In the 2011 State of the Union address, President Obama set up a goal of having 1 million EVs on the road by 2015. Based on the actual market penetration, the goal was met less than 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 interdependence between the two sides of the market (EVs and charging stations) can be characterized as indirect network effects (or the chicken-and-egg problem): the benefit of adoption/investment on one side of the market increases with the network size of the other side of the market.

The objective of this study is to empirically quantify the importance of indirect network effects on both sides of the EV market and examine their policy implications. This is important for at least two reasons. First, while industry practitioners and pol-

1. Holland, Mansur, and Muller (2015) find considerable heterogeneity in environmental benefits of EV adoption depending on the location and argue for regionally differentiated EV policy.

2. From 1996 to 1998, GM introduced over 1,000 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: the Chinese government set up a goal of half a million EVs on the road by 2015 and 5 million by 2020. The German government developed an initiative to reach 1 million EVs by 2020.

icy makers often use the chicken-and-egg metaphor to characterize the challenge faced by this technology, we are not aware of any empirical analysis on this issue. Examining the presence and the magnitude of indirect network effects is important in understanding the development of the EV market. If indirect network effects exist on both sides of the market, feedback loops arise. The feedback loops could exacerbate shocks, whether positive or negative, on either side of the market (e.g., gasoline price changes or government interventions) and alter the diffusion path. Ignoring feedback loops could lead to underestimation of the impacts of policy and nonpolicy shocks in this market.

Second, indirect network effects could have important policy implications. As we describe below, policy makers in the United States and other countries are employing a variety of policies to support the EV market. When promoting consumer adoption of this technology, they can subsidize EV buyers or charging station investors or a combination of the two. Both our theoretical and empirical analyses show that the nature of indirect network effects largely determines the effectiveness of different policies. Therefore, understanding indirect network effects could help develop more effective policies to promote EV adoption.

Taking advantage of a rich data set of quarterly new EV sales by model and detailed information on public charging stations in 353 Metropolitan Statistical Areas (MSAs) from 2011 to 2013, we quantify indirect network effects on both sides of the market by estimating two equations: a demand equation for EVs that quantifies the effect of the availability of public charging stations on EV sales, and a charging station equation that quantifies the effect of the EV stock on the deployment of charging stations. Recognizing the endogeneity issue due to simultaneity in both equations, we employ an instrumental variable strategy to identify indirect network effects. To estimate the network effects of charging stations on EV adoption, we use a Bartik (1991)–style instrument for the endogenous number of electric charging stations, which interacts national charging station deployment shock with local market conditions: number of grocery stores and supermarkets. To estimate the network effects of EV stock on charging station deployment, we use current and historic gasoline prices to instrument for the endogenous cumulative EV sales. Across various specifications, our analysis finds statistically and economically significant indirect network effects on both sides of the market. The estimates from our preferred specifications show that a 10% increase in the number of public charging stations would increase EV sales by about 8%, while a 10% growth in EV stock would lead to a 6% increase in charging station deployment.

With the parameter estimates, we examine the effectiveness of the federal income tax credit program which provides new EV buyers a federal income tax credit of up to \$7,500.[4] Our simulations show that the \$924.2 million subsidy program contributed

4. Throughout our analysis, we treat the tax credit as a full-amount rebate due to the lack of household-level data in our analysis. EV buyers are more affluent than average vehicle buyers,

to 40.4% of the total EV sales during this period. Importantly, our analysis shows that feedback loops resulting from indirect network effects in the market accounted for 40% of that sales increase, a significant portion. Our simulations further show that if the $924.2 million tax incentives were used to build charging stations instead of subsidizing EV purchase, the increase in EV sales would have been twice as large. The better cost effectiveness of the subsidy on charging stations relative to the income tax credit for EV buyers is due to (1) strong indirect network effects on EV demand and (2) low price sensitivity of early adopters.

This study directly contributes to the following three strands of literature. First, our study adds to the emerging literature on consumer demand for electric vehicles. The Congressional Budget Office (CBO 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 and finds that the tax credit could contribute to nearly 30% of future EV sales. DeShazo, Sheldon, and Carson (2014) use a statewide 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. They estimate that the current rebate policy in California that offers all income classes the same rebate of $2,500 for battery electric vehicles (BEVs) and $1,500 for plug-in hybrid vehicles (PHEVs) leads to a 7% increase in EV sales. Using market-level sales data, our study offers a first analysis to quantify the role of indirect network effects in the market and their implications on government subsidies.

Second, our study fits into the rich literature on indirect network effects. Previous work on indirect network effects dates back to early theoretical studies such as Rohlfs (1974), Farrell and Saloner (1985), and Katz and Shapiro (1985). Our paper is also related to the emerging literature on two-sided markets that exhibit indirect network effects.[5] Theoretical work includes Caillaud and Jullien (2003), Armstrong (2006), Hagiu (2006), Rochet and Tirole (2006), and Weyl (2010), and empirical work includes the PDA and compatible software market by Nair, Chintagunta, and Dube (2004), the market of CD titles and CD players by Gandal, Kende, and Rob (2000), the Yellow Pages industry by Rysman (2004), and the video game industry by Clements and Ohashi (2005), Corts and Lederman (2009), Lee (2013), and Zhou (2014). In this

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and their tax liability is likely to be over $7,500. According to the California Plug-in Electric Vehicle Owner Survey (2014), among buyers of conventional new vehicles, 15% of households have annual household income over $150,000 while among EV buyers, that share is 54% (https://energycenter.org/clean-vehicle-rebate-project/vehicle-owner-survey/feb-2014-survey).

5. Although exhibiting indirect networks, the EV market differs from the canonical two-sided markets in that there is no well-defined platform for buyers and sellers to interact. The automakers sell EVs to consumers directly. Public charging stations serve as a backup to home charging (e.g., a complementary good). The automakers do not charge charging stations loyalty fees or membership fees, as is often the case in a two-sided market.

strand of literature, our study is closest to Corts (2010) in topic which extends the literature to the automobile market and studies the effect of the installed base of flexible-fuel vehicles (FFV) on the deployment of E85 fueling stations. Corts (2010) only focuses on indirect network effects on one side of the market and does not look at that the effect of E85 fueling stations on FFV adoption.

Third, our analysis contributes to the rich literature on the diffusion of vehicles with advance fuel technologies (e.g., hybrid vehicles) and alternative fuels (e.g., FFVs). Kahn (2007), Kahn and Vaughn (2009), and Sexton and Sexton (2014) examine the role of consumer environmental awareness and signaling in the market for traditional hybrid vehicles. Heutel and Muehlegger (2012) study the effect of consumer learning in hybrid vehicle adoption, focusing on the different diffusion paths of Honda Insight and Toyota Prius. Several recent studies have examined the impacts of government programs both at the federal and state levels in promoting the adoption of hybrid vehicles, including Beresteanu and Li (2011), Gallagher and Muehlegger (2011), and Sallee (2011). Both hybrid vehicles and EVs represent important steps in fuel economy technology. Environmental preference, consumer learning, and government policies are likely to be all relevant in the EV market. Our paper focuses on the key difference between these two technologies: indirect network effects in the EV market. Huse (2014) examines the impact of government subsidy in Sweden on consumer adoption of FFVs and the environmental impacts when consumers subsequently choose to use gasoline instead of ethanol due to low gasoline prices. Based on naturalistic driving data, Langer and McRae (2014) show that a larger network of E85 fueling stations would reduce the time cost of fueling and hence increase the adoption of FFVs.

Section 1 briefly describes the industry and policy background of the study and the data. Section 2 presents a simple model of indirect network effects and uses simulations to show how feedback loops amplify shocks. Section 3 lays out the empirical model. Section 4 presents the estimation results. In section 5, we present the policy simulations and compare the existing income tax credit policy with an alternative policy. Section 6 concludes.

1. INDUSTRY AND POLICY BACKGROUND AND DATA

In this section, we first present industry background, focusing on important barriers to EV adoption and then discuss current government policies. Next we present the data used in the empirical analysis.

1.1. Industry Background

Tesla Motors played a significant role in the comeback of electric vehicles by introducing Tesla Roadster, an all-electric sports car, in 2006 and beginning general production in March 2008. However, the model had a price tag of over $120,000, out of the price range for average buyers. Nissan Leaf ($33,000) and Chevrolet Volt ($41,000) were introduced into the US market in December 2010, marking the beginning of the mass market for EVs.

There are currently two types of EVs: battery electric vehicles (BEVs) which run exclusively on high-capacity batteries (e.g., Nissan Leaf), and plug-in hybrid vehicles (PHEVs) which use batteries to power an electric motor and use another fuel (gasoline) to power a combustion engine (e.g., Chevrolet Volt). As depicted in figure 1, 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, while 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 0.82% (or 113,889) of the total new vehicle sales in the United States in 2015, and there are only about 12,500 public charging stations as of March 2016, compared to over 120,000 gasoline stations.

There are several commonly cited barriers to EV adoption. First, EVs are more expensive than their conventional gasoline vehicle counterparts. The manufacturer's suggested retail prices (MSRP) for the 2015 model of Nissan Leaf and Chevrolet Volt are $29,010 and $34,345, 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

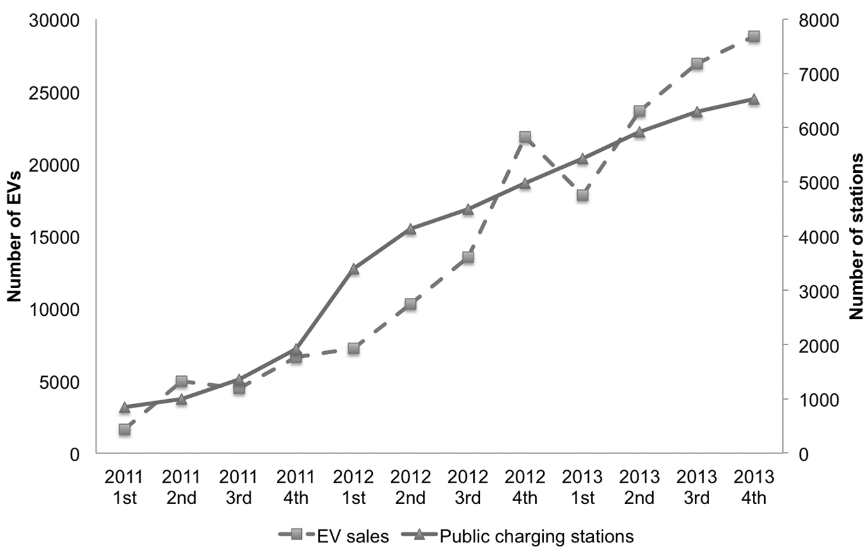

Figure 1. National quarterly EV sales and public charging stations. The quarterly EV sales plotted include both BEV and PHEV sales. Source: Authors' calculations using Hybridcars .com monthly sales dashboard data and electric charging station location data by Alternative Fuel Data Center of the Department of Energy.

cost of the battery. As battery technology improves, the cost should come down. In addition, lower operating costs of EVs can significantly offset the high initial purchase costs.[6] A recent study by EPRI (2013) compares the lifetime costs (including purchase cost less incentives, maintenance, and operation) of vehicles of different fuel types and finds that under reasonable assumptions, higher capital costs are well balanced by savings in operation costs: EVs are typically within 10% of comparable hybrid and conventional gasoline vehicles.

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. Nissan Leaf, the most popular BEV in the United States, has an EPA-rated range of 84 miles on a fully charged battery in 2015. 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 third barrier, closely related to the second, is the lack of charging infrastructure. A large network of charging stations can reduce range anxiety and allow PHEVs to operate more under the all-electric mode to save gasoline.[7] 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. The installation of charging stations involves a variety of costs, including charging station hardware, other materials, labor, and permits. A typical level 2 charging station for public use has three to four charging units and costs about $27,000, while a DC fast charging station costs over $50,000.[8] Charging stations can be found at workplace parking lots, shopping centers, grocery stores, restaurants, dealers, and existing gaso-

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6. For a regular EV such as Nissan Leaf, the fuel cost of traveling 100 miles is about $3.6 assuming that it takes 30 kilowatt hours (kWh) to drive the distance and the electricity price is 12 cents per kWh. For a conventional gasoline vehicle, the fuel cost is about $14 assuming the fuel economy of 25 mpg and gasoline price at $3.5 per gallon.

7. According to the California Plug-in Electric Vehicle Owner Survey (2014), 71% of EV owners expressed dissatisfaction with public charging infrastructure, coming down from 83% in 2012 (https://energycenter.org/clean-vehicle-rebate-project/vehicle-owner-survey/feb-2014-survey).

8. According to the charging station cost report by US Department of Energy Vehicle Technologies Office (2015), the cost of a level 2 EV charging unit for public use is between $3,000 and $6,000, and the installation fee is from $600 to $12,700 per unit. Using the average equipment cost ($ 4,500) and installation fee ($3,000) per unit, the total cost of installing a charging station of an average size (3.6 charging units) comes at $27,000. This estimate does not include future maintenance and operating cost and is therefore a lower bound estimate. Note 28 provides a upper bound estimate, which includes those costs. See "Costs Associated with Non-residential Electric Vehicle Supply Equipment" (http://www.afdc.energy.gov/uploads/publication/evse_cost_report_2015.pdf).

line stations, a point that we will come back to when constructing the instrument for the number of charging stations in the EV demand estimation. 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.

The fourth 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 (e.g., it takes 21 hours for a Nissan Leaf to get fully charged). To get faster charging, BEV drivers either need to install a charging station at home or go to public charging stations. It takes six to eight hours to fully charge a Nissan Leaf at a level 2 charging station and only 10–30 minutes at a DC fast charging station.[9] Unlike BEVs, PHEV batteries can be charged not only by an outside electric 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.

1.2. Government Policy

The diffusion of electric vehicles together with a clean electricity grid can be an effective combination in reducing local air pollution, greenhouse gas emissions, and oil dependency. The EV technology is widely considered as representing the future of passenger vehicles. The International Energy Agency projects that by 2050, EVs have the potential to account for 50% of light duty vehicle sales.[10] Many countries around the world have developed goals to develop the EV market and provide support to promote the diffusion of this technology (Mock and Zhang 2014).[11]

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 a federal income tax credit for new qualified EVs. The

9. Consumers do not need to wait for the battery to get fully charged before operating their vehicles again. They can recharge batteries by a certain amount depending on the duration of their stay at the charging locations while working, shopping, or running errands. Public charging stations mainly serve as a backup or complementary charging option to alleviate EV drivers' range anxiety. A concern toward DC fast charging is that it can reduce battery life due to the nature of charging. In addition, DC fast charging on a large scale can create demand spikes on the local electricity grid and exacerbate peak demand.

10. Hydrogen vehicles (not yet mass produced) will account for the majority of the remainder (https://www.iea.org/publications/freepublications/publication/EV_PHEV_Roadmap.pdf).

11. The Chinese government provides a rebate of over $9,000 to BEV buyers and nearly $8,000 for PHEV buyers. The UK government offers a grant of up to $7,800 to EV buyers. In Japan, EV buyers were eligible for a subsidy of up to $10,000 in 2013 and $8,500 in 2014.

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 nonmonetary incentives such as high occupancy vehicle (HOV) lane access, toll reduction, and free parking. California, through the Clean Vehicle Rebate Project, offers a $2,500 rebate to BEV buyers and a $1,500 rebate to PHEV buyers. In addition, federal, state, and local governments provide funding to support charging station deployment. For example, the Department of Energy provided ECOtality Inc. a $115 million grant to build residential and public charging stations in 22 US cities in collaboration with local project partners.

Government intervention in this market could be justified from the following perspectives. First, indirect network effects in the EV market represent a source of market failure since marginal consumers/investors only consider the private benefit in their decision, and the network size on both sides is less than optimal (Liebowitz and Margolis 1995; Church, Gandal, and Krause 2002). In addition, given the nature of the market, each side of the market is unlikely to internalize the external effect on the other side through market transactions. If EVs are produced by one automaker, the automaker would have an incentive to offer a charging station network to increase EV adoption. Nissan and GM are the two early producers of EVs, but more and more auto makers are entering the competition. Nissan is a large owner of charging stations but GM is not.[12]

Second, the external costs from gasoline consumption in the United States and many countries around the world are not properly reflected by the gasoline tax (Parry and Small 2005; Parry et al. 2014). Compared to conventional gasoline vehicles, EVs offer environmental benefits when the electricity comes from clean generation such as renewables. In regions that depend heavily on coal or oil for electricity generation, EVs may not demonstrate an environmental advantage over gasoline vehicles.[13] Electricity generation continues to become cleaner around the world due to the adoption of abatement technologies (e.g., scrubbers), the deployment of renewable generation, and the switch from coal to natural gas. In addition, technologies are being developed

12. Tesla is building its own proprietary network for Tesla owners only. This suggests that they recognize the importance of charging stations in EV adoption, but this would create duplicate systems.

13. Zivin, Kotchen, and Mansur (2014) estimate marginal CO_2 emissions of electricity production that vary by location and time of the day, and they find that charging EVs in some regions (the upper Midwest) during the recommended off-peak hours of midnight to 4 a.m. even generates more carbon emissions than the average conventional gasoline vehicle on the road. The environmental benefit of EVs under a different fuel mix of electricity generation is still an active research topic, and a critical element that has not been well understood in the literature is what types of vehicles (hybrid or gasoline vehicles) EVs replace.

to integrate EVs and renewable electricity generation such as solar and wind. The integration of the intermittent energy source with EV charging not only can help EVs fully realize its environmental benefits but also can leverage EV batteries as a storage facility to address the issue of intermittency and serve as an energy buffer (Lund and Kempton 2008).

Third, technology spillovers among firms often exist, especially in the early stage of new technology diffusion (Stoneman and Diederen 1994). The development of EV technology requires significant costs, but the technology know-how once developed can spread through many channels, including worker migration and the product market. Bloom, Schankerman, and van Reenen (2013) estimate that the social returns to R&D are larger than the private returns due to positive technology spillovers, implying underinvestment in R&D. In addition, the social returns to R&D by larger firms are larger due to stronger spillovers.

1.3. Data

We construct a panel data set consisting of quarterly EV sales by vehicle model and the number of charging stations available at 353 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 are 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, Tesla 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.

For our analysis, we focus on the 353 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 2 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, with 5,608 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 (nine EVs with a population of a quarter of a million).

We obtain detailed information on locations and open dates of all charging stations from the Alternative Fuel Data Center (AFDC) of the Department of Energy. By

Table 1. Summary Statistics

Variable	Mean	SD
A. Vehicle demand equation:		
Sales of an EV model	9.62	40.01
Gasoline prices ($)	3.52	.26
EV retail price − tax incentives ($)	33,161	18,569
No. of charging stations	22.13	45.74
Residential charging stations from the EV project	9.21	65.41
Annual personal income ($)	41,607	82,536
Hybrid vehicle sales in 2007	945	1,859
No. of grocery stores	278	624
Average commute (minutes)	22.96	3.37
College graduate share	.40	.07
Use public transport to work share	.02	.03
Drive-to-work share	.88	.05
Share of white residents	.78	.11
No. of observations	14,563	
B. Charging station equation:		
No. of charging stations	9.94	28.13
No. of EV installed base	134	584
Charging station tax credit (%)	4.56	14.7
Public funding or grants	.33	.47
No. of grocery stores	186	455
Hybrid vehicle sales in 2007	568	1,354
Current gasoline prices ($)	3.49	.27
Gasoline price last year ($)	3.25	.39
Gasoline price two years ago ($)	2.78	.59
Gasoline price three years ago ($)	2.78	.58
State EV incentives (rebates + tax credits) ($)	1,575	3,121
No. of observations	4,236	

matching the ZIP code of each charging station to an MSA and using the station open date, we construct the total number of public charging stations available in each quarter for each MSA. Panel *B* of figure 2 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 are Corvallis, OR, Olympia, VA, and Napa, CA, with 210, 170, and 117 public charging stations per million people, respectively. These three MSAs are the number eleventh, fifth, and sixth in terms of the EV concentration in panel A.

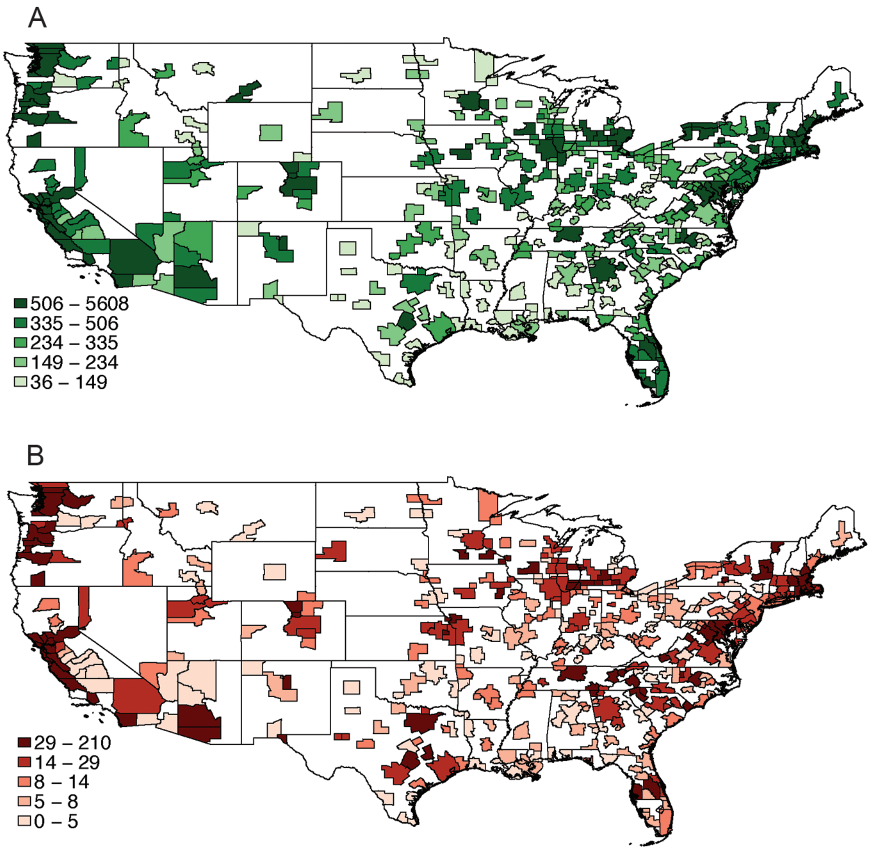

Figure 2. Spatial distribution of EVs and public charging stations. *A*, Installed base of EVs per million people. *B*, Public charging stations per million people. Map boundaries define metropolitan statistical areas. Both graphs are shown for the fourth quarter of 2013.

We collect data on state-level incentives such as tax credits and rebates for both electric vehicles and 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. Household demographics are collected from the American Community Survey.

2. A MODEL OF INDIRECT NETWORK EFFECTS

In this section, we use a stylized model to illustrate indirect network effects on both sides of the market (EV demand and charging station investment) and to show how indirect network effects give rise to feedback loops. We then conduct simulations to shed light on how the effectiveness of different types of policies (e.g., subsidizing EV purchases versus charging station investment) hinges on the relative magnitude of indirect network effects on the two sides as well as consumer price sensitivity. The results from the simulations provide a theoretical basis for our empirical findings based on real-world data.

2.1. Model Setup and Properties

We assume that EV sales $q_t(N_t, p_t, x_t)$ depends on the number of public charging stations in the market (N_t), the price of the EV (p_t), and other product characteristics combined (x_t) that affect consumers' choice, such as the fuel cost.[14] The installed base of EVs is the cumulative sum of EV sales minus scrappage by the time t, denoted by $Q_t = \Sigma_{h=1}^{t} q_h * s_{t,h}$, where $s_{t,h}$ is the survival rate at time t for EVs sold in time h. The number of charging stations that have been built $N_t(Q_t, z_t)$ depends on the EV market size Q_t and other variables combined z_t that might affect the fixed cost of investment. To facilitate the illustration, we specify the following functions for EV demand and charging station deployment:

$$\ln(q_t) = \beta_1 \ln(N_t) + \beta_2 \ln(p_t) + \beta_3 x_t, \tag{1}$$

$$\ln(N_t) = \gamma_1 \ln(Q_t) + \gamma_2 z_t. \tag{2}$$

The EV demand equation arises from a discrete choice model of vehicle demand and follows closely the logit model using the market-level data as in Berry (1994). The charging station equation can be derived from an entry model as in Gandal et al. (2000), and we derive an empirical counterpart to this equation for our specific context in the appendix.

The parameters β_1 and γ_1 capture the magnitude of the indirect network effects on the two sides. Feedback loops (or two-way feedback) arise if both β_1 and γ_1 are nonzero. Intuitively, a shock to the system, for example, an increase in x_t, would change EV sales q_t, which would in turn affect 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 both β_1 and γ_1 are positive, positive feedback loops would arise, and they can amplify the shocks (either positive or negative) in either side of the market, such as a tax credit for EV purchases or subsidy on charging station investment. The parameter β_2 (negative) is the price elasticity of demand and captures consumer price sensitivity.

To understand the property of the system such as the existence of the steady state and its property, we assume that the survival rate $s_{t,h}$ is δ^{t-h}, where $\delta < 1$. Further

14. We assume that there is only one EV model to ease exposition. Our empirical analysis is at the vehicle model level and uses a richer specification.

assume $p_t = p$, $x_t = x$, and $z_t = z$. Substituting equation (2) into equation (1), we have:

$$\ln(q_t) - \beta_1\gamma_1 \ln(q_t + \delta Q_{t-1}) = \beta_1\gamma_2 z + \beta_2 \ln(p) + \beta_3 x. \tag{3}$$

The right-hand side $\beta_1\gamma_2 z + \beta_2 \ln(p) + \beta_3 x$ is constant with respect to q_t, and we denote it by c. During period 1, $Q_{t-1} = 0$. Solving the equation, we obtain $q_1 = \exp[c/(1 - \beta_1\gamma_1)]$. To solve for the steady state solution (q^*, N^*), we use the steady state condition $q_t = q_{t+1} = q^*$ and find:

$$q* = \exp\left(\frac{c - \beta_1\gamma_1 \ln(1-\delta)}{1-\beta_1\gamma_1}\right) = q_1 * \exp\left(\frac{-\beta_1\gamma_1 \ln(1-\delta)}{1-\beta_1\gamma_1}\right).$$

$$N^* = \exp\left[\gamma_1 \frac{c - \beta_1\gamma_1 \ln(1-\delta)}{1-\beta_1\gamma_1} - \gamma_1 \ln(1-\delta) + \gamma_2 z\right].$$

The stock of EVs in the steady state $Q^* = q^*/(1-\delta)$ where the outflow of EVs due to scrappage is equal to the inflow from new EV sales.[15] To examine the stability of the steady state, we write $Q_{t-1} = q_{t-1} + \delta Q_{t-2}$ and substitute it into equation (3): $\ln(q_t) - \beta_1\gamma_1 ln(q_t + \delta q_{t-1} + \delta^2 Q_{t-2}) = c$. This defines an implicit function of $q_t = G(q_{t-1})$. When $\beta_1\gamma_1 < 1$, it can be shown that $G(0) > 0$, $G'() > 0$, and $G''() < 0$. Therefore, the steady state solution is stable as shown in figure 3. In our following policy analysis, we take $\beta_1\gamma_1 < 1$, which is also confirmed in our empirical analysis.

The partial effect of vehicle price p on EV sales in the steady state is:

$$\frac{\partial q^*}{\partial p} = \exp\left(\frac{c - \beta_1\gamma_1 \ln(1-\delta)}{1-\beta_1\gamma_1}\right)\frac{\beta_2}{1-\beta_1\gamma_1},$$

where $\beta_2 < 0$. When $\beta_1\gamma_1 < 1$, this partial effect is negative as economic theory would suggest. Similarly, the changes in other demand side factors captured by x and the changes in the factors in the charging station equation z will both shift $G(q_{t-1})$ in figure 3 up or down and hence affect the steady state solution of EV sales.

2.2. Implications on Policy Choices

Now we conduct simulations to understand how feedback loops magnify policy shocks and their implications on policy choices. We fix p_t, x_t, and z_t in equations (1) and (2)

15. Alternatively, the steady state can be equivalently expressed in terms of (Q^*, N^*). Our specification rules out (0, 0) as another steady state solution. Having multiple equilibria is often a signature property of two-sided markets with indirect network effects due to self-confirming expectations (e.g., Gandal et al. 2000). From an empirical perspective, our specification is without loss of generality since the empirical studies in this literature often assume that the nonzero stable solution plays out in the data.

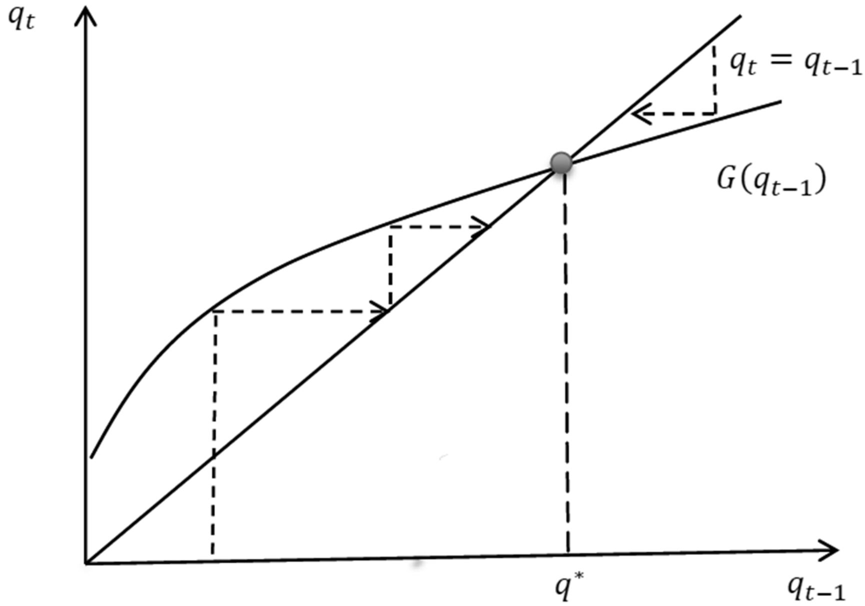

Figure 3. Steady state solution and stability. The expression q_t is the number of new EV sales in each period; $q_t = G(q_{t-1})$ is the implicit function defined in equation (3); q^* is the steady state solution.

and assume certain values for model parameters as reported in table 2. We then solve for q_t, Q_t, and N_t sequentially for each period. Because of the positive feedback loops (by assuming both β_1 and γ_1 being positive), EV sales and the number of charging stations will keep growing naturally until they reach the steady state where the inflow of new vehicles equals the outflow of vehicles due to scrappage. To examine how positive feedback loops could amplify a policy shock, we simulate a scenario where all EV buyers are provided with a $7,500 subsidy for the first five periods and no more subsidy is offered afterward.

As shown in panel *A* in figure 4, due to both the price effect (captured by β_2) and the indirect network effects (captured by β_1 and γ_1), the subsidy increases EV sales substantially compared with the no-policy case during the first five periods. When the subsidy terminates, EV sales continue to increase through feedback loops but with a smaller magnitude. The sales increase due to subsidy gets smaller as feedback loops diminish and the two growth paths eventually overlap. In both cases, the path of EV sales converges to the same steady state but the policy shock makes the system converge to the steady state more quickly: indirect network effects expedite this process through positive feedback loops.

Table 2. Parameters for Simulating Indirect Network Effects

Coefficients	Values	Variables	Values
β_1	.8	p	30,000
β_2	−1.5	X	16
β_3	1	Z	2
γ_1	.4		
γ_2	1		
δ	.9		

Figure 4, panel *B*, depicts a similar pattern in the dynamic path of charging station deployment. With the positive policy shock on the EV purchase side, the stock of charging stations increases quickly for the first five periods and continues to grow at a decreasing rate after the policy. It eventually converges to the same steady state as in the no-policy scenario. These two graphs demonstrate that feedback loops from indirect network effects magnify a shock to any side of the system and alter the convergence process on both sides.

The existence of indirect network effects on both sides of the market could have important policy implications. To foster the development of the EV market, policy makers can choose to subsidize consumers for EV purchase directly (policy 1) or to subsidize charging station investment (policy 2). We conduct simulations to examine the relative cost effectiveness of these two policy options. Policy 1 provides EV buyers with a subsidy of $7,500 per EV in the first five periods. Policy 2 uses the same account of total funding as in policy 1 to build charging stations. We compare the cumulative sales increase over time due to these two policies (with a 5% annual discount rate).[16]

To examine the implication of the relative strength of indirect network effects on policy choices, we vary the ratio of β_1/γ_1 by holding β_1 constant while changing γ_1. Figure 5 depicts, for any given price sensitivity β_2 (say −1.5), as β_1/γ_1 increases (i.e., indirect network effects in EV demand become relatively stronger), the second policy (subsidy on charging stations) becomes more and more effective measured by the increase in cumulative sales over time. The two policies are equivalent when β_1/γ_1 is 1 given the price elasticity of −1.5.

16. For policy 1, we subtract the EV price by $7,500 to simulate the counterfactual sales in the first five periods. The total expenditure of the subsidy policy is then calculated by multiplying $7,500 with the total EV sales for the five periods. By assuming the cost of building one charging station to be $27,000, we obtain the total number of charging stations that could be built with the same amount of funding. We assume that the investment occurs evenly each year over the first five periods and we add the number of charging stations that could be funded to N_t to simulate the counterfactual outcomes under policy 2.

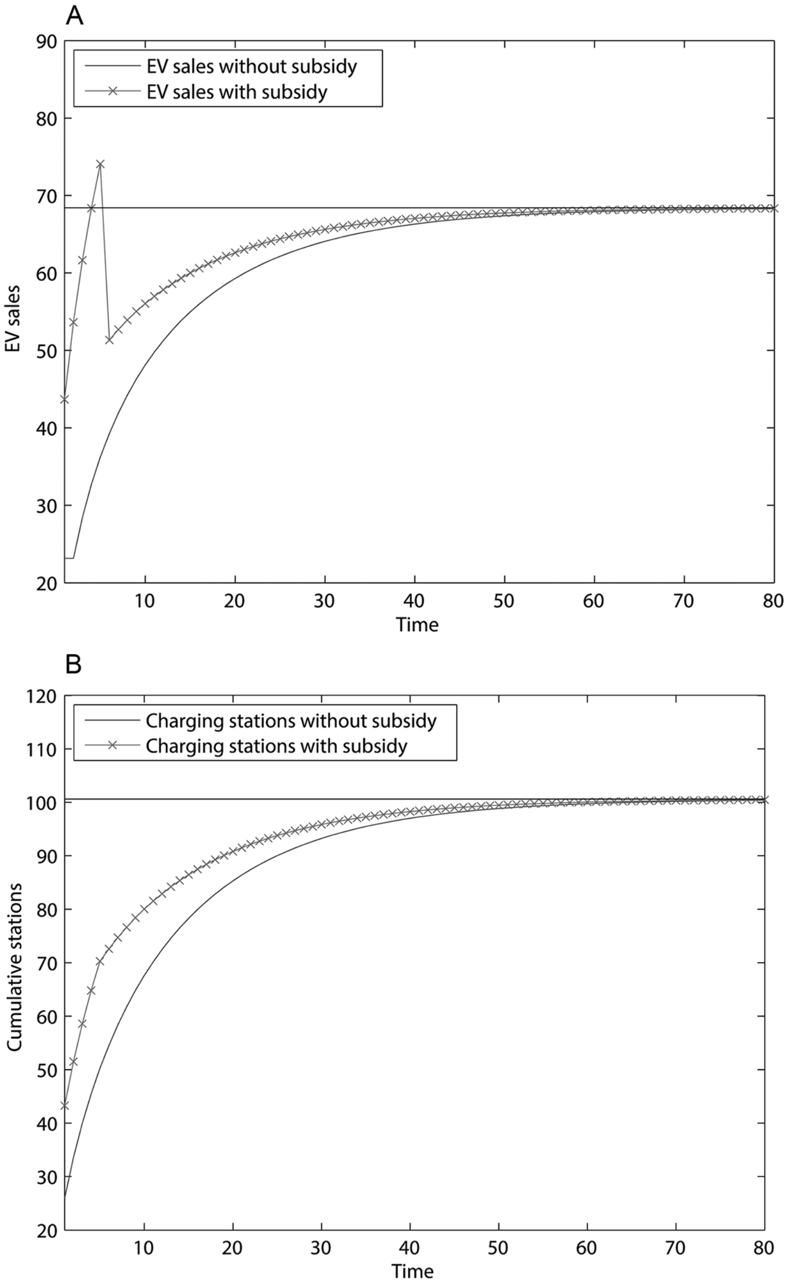

Figure 4. Impacts of income tax credits (five periods) under feedback loops. *A*, EV sales increase due to feedback loops. *B*, Charging stations increase due to feedback loops. EV sales and charging stations without subsidy are solutions given by the system defined in section 3. The simulated subsidy effects are due to a policy design that gives EV buyers a tax credit of $7,500 for the first five periods. The parameters for simulations are reported in table 2, and the intuitive findings remain with different assumptions of the simulation parameters.

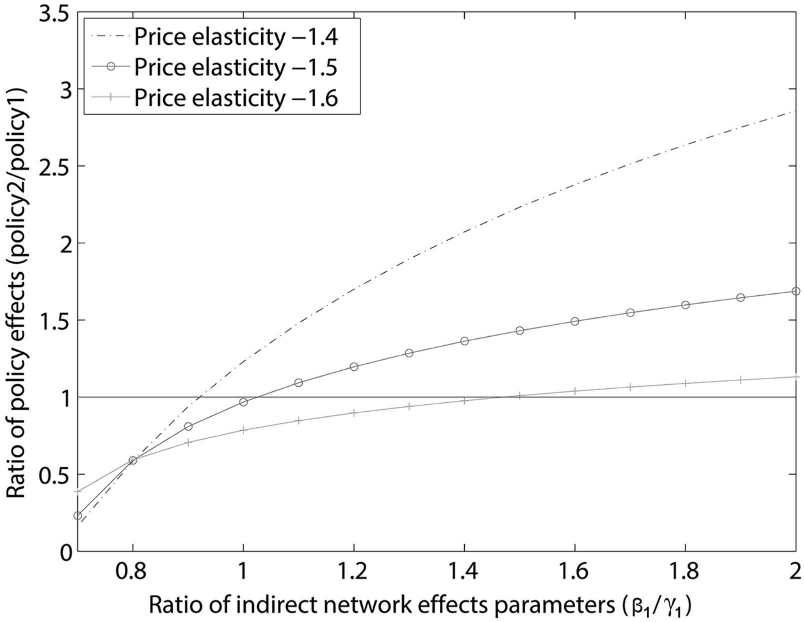

Figure 5. Policy comparison and relative strength of indirect network effects. This figure depicts the relationship between the relative policy effects of two subsidy designs and the relative strength of the indirect network effects on both sides of the EV market. Policy 1 subsidizes the EV purchase by tax credits and policy 2 uses the same amount of funding to subsidize charging stations. Given a price elasticity of EVs, policy 2 becomes more and more effective than policy 1 when the effect of charging stations on EV demand (denoted by β_1) becomes larger relative to the effect of EV stock on charging stations (denoted by γ_1). When the magnitude of the price elasticity increases (decreases) and consumers are more (less) sensitive to prices, policy 2 becomes less (more) effective relative to policy 1 for a given ratio of β_1/γ_1.

In addition to the relative strength of indirect network effects on both sides, the policy comparison also depends on the price elasticity of EV demand. When consumers are more sensitive to prices (e.g., going from −1.5 to −1.6), the policy of subsidizing charging stations becomes relatively less effective for a given β_1/γ_1. This finding is illustrated by the outward shift of the curve when the price elasticity changes to −1.4 and −1.6. The result is intuitive: if consumers are less price sensitive, it would take a larger subsidy on EV purchases in order to push consumers to buy EVs, hindering the effectiveness of the policy.

To summarize, the policy of subsidizing charging stations becomes more effective relative to the policy of subsiding EV purchases when indirect network effects on EV demand become stronger (holding network effects on the charging station side constant) or when consumers are less sensitive to price. These findings offer a theoretical foundation for the policy comparison after our empirical analysis.

3. EMPIRICAL FRAMEWORK

To investigate indirect network effects on both sides of the market, we estimate: (1) an EV demand equation that examines the effect of charging stations on EV sales and (2) a charging station equation that estimates the effect of athe EV fleet on charging station deployment. These equations build upon equations (1) and (2) in the theoretical model above.

3.1. EV Demand

To describe the empirical demand model of EVs, let k index an EV model such as Nissan Leaf and Chevrolet Volt, m index a market (MSA), and t index a year-quarter. We estimate the following equation:

$$\ln(q_{kmt}) = \beta_0 + \beta_1 \ln(N_{mt}) + \beta_2' X_{kmt} + T_t + \delta_{km} + \varepsilon_{kmt}, \tag{4}$$

where q_{kmt} is the sales of EV model k in market m and year-quarter t.[17] The term N_{mt} denotes the total number of public charging stations that have been built in the MSA by the end of a given quarter.[18] 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. The expression $\ln(N_{mt})$ captures the effect of charging stations on electric vehicle purchases and the log form allows the effect to be diminishing. The term X_{kmt} is a vector of related covariates including the effective purchase price, personal income, and other control variables. The effective purchase price of a model is defined as the manufacturer's suggested retail price (MSRP) less the related subsidies (tax credits and tax rebates at both federal and state levels).

We also include a full set of year-quarter (e.g., the first quarter of 2011) fixed effects and MSA model (e.g., Nissan Leaf in San Francisco) fixed effects in equation (4). Year-quarter fixed effects T_t control for national demand shock for EVs common across MSAs such as consumer awareness. MSA-model fixed effects δ_{km} not only control for time-invariant product attributes such as quality and brand loyalty that could

17. This empirical specification is taken to be consistent with our theoretical model and to ease results interpretation. The logit model from Berry (1994) implies that the dependent variable would be $\ln(s_{kit}) - \ln(s_{0mt})$ where s_{kmt} is the market share of model k in market m and time t and s_{0mt} is the share of consumers who are not purchasing an EV. These two specifications provide almost identical parameter and elasticity estimates (see table 6).

18. In the estimation, we add one to q_{kmt}, N_{mt} to deal with zero values for some of the observations. Our results are robust to excluding observations with zero values on q_{kmt} or N_{mt} and using $\ln(q_{kmt})$ and $\ln(N_{mt})$.

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). The term ε_{kmt} 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).

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, Levinsohn, and Pakes 1995; Beresteanu and Li 2011). MSA-model fixed effects absorbs both observed and unobserved vehicle attributes variations that are time invariant, and what is left is the variation of vehicle attributes over time. Since most of the EV models in our sample appear for only one year and there is little variation of the observed attributes for the models that appear for more than one year, we believe that using MSA-model fixed effects could control for unobserved product attributes and alleviate 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).[19] The price coefficient is identified from the fact that effective EV prices vary across markets and over time due to state-level subsidies and temporal price variations.

Although we include a rich set of control variables, the charging station variable is still endogenous due to simultaneity: the unobserved time-varying and market-specific demand shocks could affect charging station investment decisions and hence the stock of charging stations. To deal with the endogeneity, we use the IV strategy, and a valid IV needs to be correlated with the number of charging stations in an MSA (the endogenous variable) but not correlated with the unobserved shocks to EV demand. The IV we employ is the interaction term between the number of grocery stores and supermarkets in an MSA in 2012 with the number of charging stations in all MSAs other than the MSA corresponding to a given observation (lagged for one quarter). Grocery stores and supermarkets are a major owner of charging stations, and they build charging stations 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 shopping. Nissan has been actively partnering with grocery store owners to build charging stations. Kroger, the country's largest grocery store owner, has installed about 300 charging stations in their stores across the coun-

19. 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 observed product attributes, which could be a strong assumption (Klier and Linn 2012). As a robustness check, we also include electric range and electric mpg in one of the alternative specifications and the results are qualitatively the same.

try. Our data show 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 fixed effects. To introduce temporal variation, we multiply it with the lagged number of existing charging stations in all MSAs other than the MSA corresponding to a given observation, which captures the national-level trend in charging station investment due to aggregate shocks such as temporal variations in costs, investor confidence, and federal incentive programs. The construction of this IV is similar in spirit to the Bartik instrument used in the labor literature to isolate local labor demand changes (Bartik 1991). The intuition for the IV is that national shocks to charging station investment (captured by the lagged number of charging station in all MSAs other than own) have disproportional effects on charging station investment across MSAs: 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 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 fixed effects and should capture these time-invariant unobservables. At the temporal dimension, EV sales vary from year to year but the number of grocery stores is very stable given the maturity of the 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 other than the own city. Time fixed effect would control for time-varying common shocks across MSAs. Excluding the home city's charging stations also removes the concern that one MSA's installation of a large number of charging stations could overly influence the estimation results.

Our IV strategy leverages the interaction term between a national-level variable with only temporal variation and an MSA-level variable with only spatial variation. The rationale behind the IV is that different MSAs have different preexisting conditions/ability to absorb national shocks to charging station investment such as changes in macro-economic conditions and costs. One might be concerned that different MSAs may have a different susceptibility to unobservable demand shocks at the national level and the number of grocery stores could be correlated with this susceptibility for some reason. To address this concern, we include a variety of MSA-level controls interacting with the time trend. We use the sales of hybrid vehicles in 2007 (several years before EVs entered the market) to proxy for preference heterogeneity for greener vehicles or environmental friendliness. We also include personal income, the share of college graduates among residents, the share of commuters driving to work, the share of commuters using public transport to work, and the share of white residents. We use the interactions of these variables with the time trend to control for potential heterogeneity in the diffusion path of EVs across MSAs. Our results are robust to the inclusion of these controls, providing further support that our IV is a valid exclusion restriction.

In some of the robustness checks, we use local policy variables such as subsidies on charging stations as additional IVs and obtain similar results. We do not use them in our benchmark specifications due to the concern that local policies whether subsidizing charging stations or EV purchases could be a response to local unobserved demand shocks and hence be endogenous.

3.2. Charging Station Deployment

We derive the empirical model of charging station investment from an entry model presented in the appendix where the profit depends on both the installed base of EVs and the total number of charging stations in a market. Under certain functional form assumptions, the total number of charging stations in a free-entry equilibrium is given by the following equation:

$$\ln(N_{mt}) = \gamma_0 + \gamma_1 \ln(Q_{mt}^{EV}) + \gamma_2' Z_{mt} + T_t + \varphi_m + \varsigma_{mt}, \tag{5}$$

where N_{mt} denotes the stock of public charging stations that have been built in market m by time t and Q_{mt}^{EV} denotes the installed base of EVs by time t. The vector of covariates Z_{mt} includes the state-level tax credit given to charging station investors measured as the percentage of the building cost, a dummy variable indicating whether there exist public grants or funding to build charging infrastructure, the interaction term of number of grocery stores in a MSA in 2012 with the lagged number of charging stations in all MSAs other than own (the instrument in the EV demand equation), and other control variables.

We also include a full set of time and MSA fixed effects. The term T_t denotes year-quarter fixed effects to control for time-varying common shocks to charging station investment across MSAs such as macro-economic conditions. Market fixed effects φ_m 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 a limited private installment of charging stations may have more public charging stations. The term ζ_{mt} is the unobserved shock to charging station investment, for instance, the unobserved local policies to support the charging station building. In the estimation, we add one to

N_{mt} and Q_{mt}^{EV} to deal with zero values for some of the observations. We obtain similar results by dropping these observations and use $\ln(N_{mt})$ and $\ln(Q_{mt}^{EV})$ instead.

The issue of endogeneity due to simultaneity also arises in this equation. Both N_{mt} and Q_{mt}^{EV} are stock variables, but the inflows to each variable are determined at the same time. As a result, time-varying and MSA-specific shocks to investment decisions (the error term in the equation) could be correlated with current EV sales, which are part of the installed base. The instrument variables emerge more naturally in this equation. In particular, we instrument for the installed base of EVs with a set of current and past gasoline price 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.[20] Because the installed base of EVs is the cumulative sales of EVs, we include gasoline prices not only in the current quarter but annual gasoline prices in the past three years as instruments. For example, for the installed base of EVs in the second quarter in 2013, we use the gasoline price in the second 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.

These gasoline price variables (including current and past gasoline prices) should affect the installed base, which is confirmed in the first-stage regression in table 8. But they are unlikely to affect investment decisions directly (i.e., other than through the installed base). Since we include both time and MSA fixed effect, 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, which are unlikely to be correlated with charging station investment directly. The decision of charging station investment hinges on, among other things, the EV market potential (proxied by the installed base of EVs) and the fixed costs of investment. Fixed costs of charging station investment 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).

20. A report on the ownership cost of EVs by Electric Power Research Institute (2013) finds that increases and decreases in gasoline prices will have a significant impact on the relative costs of EVs.

4. ESTIMATION RESULTS

We first present parameter estimates for equations (4) and (5). We then discuss the indirect network effects implied by these parameter estimates.

4.1. Regression Results for EV Demand

Columns *a*–*e* in table 3 report the ordinary least squares (OLS) estimation results for five different specifications where we add more control variables successively (first-stage results reported in table 4). Column *a* includes only six explanatory variables. Column *b* adds in year-quarter fixed effects to control for time-varying common unobservables across MSAs. Column *c* further adds vehicle model fixed effects to control for unobserved product attributes such as quality and brand loyalty that affect consumer demand. Column *d* includes rich MSA-model fixed effects to control for both unobserved product attributes and MSA-specific demand shocks for different EV models. Column *e* adds two additional variables to control for potential heterogeneity in the diffusion pattern across MSAs. The first variable is the interaction term between the sales of hybrid vehicles in 2007 (to proxy for preference for green vehicles) and the time trend, and the second variable is the interaction between average personal income and the time trend. Column *f* implements a GMM estimation strategy and uses the interaction term of number of grocery stores and supermarkets in an MSA in 2012 with the lagged number of charging stations in all the other MSAs as the instrument for the number of charging stations.

Given the log-log specification, the coefficient estimates can be interpreted as elasticities. All the specifications provide intuitive and statistically significant coefficients on the key variables of interests: EV demand increases with a larger network of charging stations, a lower vehicle price, and more home charging stations funded by the EV project supported by the DOE, and higher income. The coefficient on the charging station variable captures indirect network effects from charging station investment on EV demand. The GMM results show that a 10% increase in charging stations would result in an 8.4% increase in EV sales, which is higher than all the OLS estimates (ranging from 1.8% to 5%). This suggests that the number of charging stations is negatively correlated with the unobserved shocks to EV demand, leading to downward bias in OLS. One example of unobserved shocks is local EV incentives that local governments provide to compensate for the lack of public charging stations. Another example is the home charging incentives from local electric utilities. Many local utilities offer a rebate for installing a home charging station and a discounted rate for home EV charging as part of the demand side management program. Local governments often partner with local utilities to provide more generous home charging incentives when there is a lack of private investment in public charging stations.

The price coefficients change from −0.470 to −0.817 from columns *b*–*c* after vehicle model fixed effects are included. This is consistent with our discussion above: vehicle model fixed effects control for unobserved product attributes which could

Table 3. EV Demand Equation

Variable	OLS (*a*)	OLS (*b*)	OLS (*c*)	OLS (*d*)	OLS (*e*)	GMM (*f*)
ln(no. of charging stations)	.378***	.389***	.502***	.352***	.177***	.844***
	(.017)	(.017)	(.021)	(.037)	(.036)	(.162)
ln(gasoline price) × PHEV	1.095***	1.186***	1.922***	.095	−.033	−.083
	(.203)	(.301)	(.353)	(.208)	(.201)	(.206)
ln(gasoline price) × BEV	.611***	.704***	1.908***	.560**	.386*	.419*
	(.203)	(.300)	(.406)	(.229)	(.217)	(.220)
ln(retail price − tax incentives)	−.480***	−.470***	−.817***	−1.378***	−1.433***	−1.288***
	(.034)	(.034)	(.179)	(.142)	(.140)	(.131)
ln(residential charging from EV project)	.046*	.035	.019	.026**	.059***	.050***
	(.025)	(.024)	(.022)	(.012)	(.011)	(.010)
ln(personal income)	.667***	.664***	.729***	2.018**	1.215*	2.056**
	(.162)	(.161)	(.179)	(.852)	(.695)	(.855)
ln(hybrid vehicle sales in 2007) × time trend					.031***	.011**
					(.003)	(.005)
ln(personal income) × time trend					.003	.001
					(.016)	(.020)
Year-quarter fixed effects	No	Yes	Yes	Yes	Yes	Yes
Vehicle model fixed effects	No	No	Yes	Yes	Yes	Yes
MSA-model fixed effects	No	No	No	Yes	Yes	Yes

Note. The number of observations is 14,563. The dependent variable is ln(EV sales) by model by quarter in an MSA. Retail prices are manufacturers' suggested retail prices. Tax incentives include both federal and state-level tax credits and tax rebates associated with EVs. All standard errors are clustered at the MSA level. ln(residential charging from the EV project) is the logarithm of quarterly number of residential charging stations that are built in an MSA by the EV Project, which is managed by ECOtality North America and supported by the US Department of Energy to deploy level 2 residential and commercial charging stations in 22 US cities. ln(hybrid vehicle sales in 2007) × time trend and ln (personal income) × time trend are included to address the concern that the charging stations trend could be correlated with potential trend of EV demand. The *p*-value for underidentification test for the last column is 0.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

Table 4. First-Stage Results for EV Demand Equation

Variable	
ln(no. of grocery stores) × ln(lagged national stations)	.139***
	(.023)
ln(retail price-tax incentives)	−.193***
	(.054)
ln(gasoline price) × PHEV	.146
	(.125)
ln(gasoline price) × BEV	.064
	(.135)
ln(residential charging from EV project)	−.011
	(.010)
ln(personal income)	−.980
	(1.035)
ln(hybrid vehicle sales in 2007) × time trend	.010***
	(.003)
ln(personal income) × time trend	.018
	(.022)
R^2	.677

Note. The dependent variable is ln(no. of stations). The number of observations is 14,563. Standard errors (in parentheses) are clustered at the MSA level. The model includes year-quarter fixed effects and MSA-model (e.g., Nissan Leaf in San Francisco) fixed effects.

* $p < .10$.
** $p < .05$.
*** $p < .01$.

be positively correlated with prices. Ignoring unobserved product attributes will bias the price coefficient toward zero. Going from columns *c*–*d* where MSA-model fixed effects are included, the EV demand function changes from being inelastic with a price elasticity of −0.817 to being elastic with a price elasticity of −1.378. MSA-model fixed effects control for MSA-specific time-invariant demand shocks (such as environmental preference), and these demand shocks could affect state-level tax incentives. For example, higher incentives are used to counter negative demand shocks. Hence MSA fixed effects could control for the potential endogeneity in state-level tax incentives. The GMM results provide a price elasticity of −1.288. Although this is at the lower end of the price elasticity estimates in the literature on automobiles, we believe that the magnitude is reasonable compared with the literature for two reasons.[21] First,

21. Berry et al. (1995) estimate the price elasticities ranging from −3 to −7 for vehicle models in 1990 with more expensive models having the smaller price elasticities (in magnitude). The

EV buyers are more affluent and hence less price sensitive compared with average vehicle buyers. Second and perhaps more importantly, EV buyers can be characterized as early adopters, and one can argue that many of them choose EVs out of their strong environmental concerns and/or making a statement by driving an EV as has been documented in the case of hybrid vehicles (e.g., Kahn 2007; Sexton and Sexton 2014).[22]

Lower fuel cost is one of the major benefits of EVs, and higher gasoline prices will have a positive impact on EV adoption by increasing future fuel cost savings from driving EVs in place of conventional vehicles. To capture the heterogeneous impact of gasoline price on the demand of the two types of EVs, two interaction terms of quarterly gasoline prices with BEV and PHEV dummy variables are included. The results from all the specifications find a positive and statistically significant effect of gasoline price on BEV purchase. While the interaction term with PHEV is positive and significant in columns *a*–*c* of table 3, columns *d*–*f* do not find a significant impact of gasoline price on PHEV demand when MSA-model fixed effects are included. Intuitively, BEV drivers could be more sensitive to gasoline prices than PHEV buyers given that BEVs run exclusively on electricity while PHEVs run mostly on gasoline for long-distance driving given its short range of battery charge. That is, PHEV drivers do not make a long-term commitment to an alternative fuel to the extent that BEV drivers do. In addition to gasoline prices, we included electricity prices in previous analysis and the coefficient estimate was small in magnitude and statistically insignificant in all specifications. This could be because (1) the operating cost from using electricity is a small portion of vehicle lifetime cost for EVs and (2) there is not much MSA-specific temporal variation in electricity prices. The coefficient on the interaction term between hybrid sales in 2007 and time trend is positive and statistically significant, implying that MSAs that had more sales of hybrid vehicles in 2007 (proxy for preference for greener products) have a faster diffusion of EVs.

The results from these regressions imply that the increased availability of public charging stations has a statistically and economically significant impact on EV adoption decisions. Our estimation results confirm that even if most EV drivers can charge vehicles at home, better access to public charging facilities elsewhere is still an important demand factor by, for example, alleviating range anxiety.[23] Based on the parameter estimates on charging station and price variables, a back-of-the-envelope calcula-

lower end of price elasticities for vehicle models in 2006 in Beresteanu and Li (2011) is also around −3.

22. The California Plug-in Electric Vehicle Owner Survey (2014) shows that EV buyers have higher household income than buyers of gasoline vehicles and that the environmental concern is an important motivator for EV purchase: 38% of Nissan Leaf buyers and 18% Chevy Volt buyers consider the environmental concern to be the top motivator.

23. According to the EV Project report (Idaho National Laboratory 2013), the percentage of EV home charging for 22 program areas is about 79% for Nissan Leaf and 84% for Chevrolet Volt.

tion shows that the demand effect from having one more charging station from the sample average of 22.6 is equivalent to that from a reduction of EV price by $961 (the average price is $33,127). When the number of charging stations increases to 27.3 (the sample average in 2013), the equivalent price reduction is $795. At the sample maximum of 320 charging stations, one more charging station is only equivalent to $68 price reduction, showing the diminishing effect implied by the log-log functional form.

4.2. Alternative Specifications for EV Demand

We take the estimates in column *f* in table 3 as our baseline specification. To check the robustness of the results, we estimate a variety of different specifications, and the results are reported in table 5. Column *a* includes the interaction term between the number of charging stations and average commute time to work in the MSA to capture the heterogeneous impact of charging stations across cities with different commuting patterns.[24] The positive coefficient estimate on the interaction term suggests that the availability of charging stations has a larger impact on EV demand in the MSAs with a longer commute. This is intuitive since in MSAs where people have a longer commute, range anxiety would be more of an issue. Across MSAs, the elasticity of charging stations with respect to the EV sales ranges from 0.27 to 1.05 depending on the average commute time.

Column *b* adds the quadratic terms of the time trend variables to our baseline specification to allow more flexible time effect. The coefficient estimates on the key parameters are almost intact. Column *c* includes the interaction term of charging stations with a BEV dummy to capture the different impact of charging stations on BEVs and PHEVs. The coefficient estimate on the interaction term is positive while not statistically significant. Column *d* includes two more instruments: the tax credits and the availability of public funding for building charging stations, both of which appear in the charging station equation. We did not include them in our baseline specification because the exogeneity assumption may not hold for the subsidies as they could be a response to unobserved EV demand shocks. Column *e* removes the price variable in the regression to deal with the concern that the price variable, especially state-level incentives, could be endogenous. Column *f* adds the interaction terms between various demographic variables and the time trend to further control for MSA-level heterogeneity in the diffusion pattern. Across these specifications, the estimated effects of charging station availability on EV demand as well as other parameter estimates are similar to those from the baseline specification in table 3. Column *g* reports the de-

24. The average commute time to work at the MSA level is calculated based on combined 2006–11 samples of the American Community Survey. The average commute time is 22.96 minutes with a standard deviation of 3.37, a minimum of 14.59 and maximum of 35.01.

mand estimation using the logit model as in Berry (1994), and it produces almost identical elasticity estimates as our baseline specification.

Some states, such as California and Oregon, have adopted a Zero Emission Vehicle (ZEV) program, which requires a certain part of automakers' sales to be clean fuel vehicles, and some automakers have introduced EV models in those regions only to comply with the regulations. To control for more intense competition in those markets due to more EV models introduced, column *h* in table 6 includes ZEV-specific time fixed effects, and the results are similar to previous results with a modest increase in the coefficient estimate on charging stations. Column *i* uses only BEV sales, and the estimates are not systematically different from the estimates using the full sample with BEVs and PHEVs. Columns *j* and *k* increase the lag of the total number of charging stations in all other MSAs to two and three-quarters when constructing the instrumental variable and there is no substantial change of the estimates except that the coefficient of the charging stations decreased slightly, primarily due to loss of observations. However, increasing the lag to more than three-quarters leads to weak IV.

As shown in column *g* in table 6, our demand specifications would yield nearly identical results as the Berry logit model. With only EV models in our data, our analysis treats all other non-EV models to be in one category (i.e., the outside good). Limiting the choice set and the substitution pattern across choices could potentially affect our estimate of the price elasticity and our policy simulations. EV models represent a different technology that is dramatically different from conventional gasoline vehicles; therefore, consumers are likely to consider them as a separate category in making purchase decisions, especially given that the EV buyers in our data period are often motivated by strong environmental concerns according to the California Plug-in Electric Vehicle Owner Survey (2014). Nevertheless, some PHEVs do have conventional hybrid counterparts. For example, the Toyota Prius plug in has a hybrid version, Toyota Prius. Considering most of PHEVs have limited electric range (11–38 miles), some consumers may compare PHEVs with hybrid vehicles. Recognizing this, column *i* in table 6 only include BEV models in the regression. The results are very similar to those obtained using the full sample, suggesting that the limitation in our choice set and modeling framework may not have a large impact on the key parameters of interest.[25]

25. EV models only represent less than 0.8% of new vehicle sales in the nation in 2013. Including models of other fuel types would not help us identify the indirect network effects since their demand does not depend on EV charging stations. We believe that micro-level data with the second-choice information is much better suited to assess the substitution pattern between EVs and different types of non-EVs than the aggregate data that we currently have. This is an ongoing work of the authors.

Table 5. Additional Specifications for Vehicle Demand, A

Variable	GMM (*a*)	GMM (*b*)	GMM (*c*)	GMM (*d*)	GMM (*e*)	GMM (*f*)
ln(no. of charging stations)	−.282	.785***	.817***	.791***	.866***	.851***
	(.243)	(.229)	(.156)	(.152)	(.165)	(.157)
ln(no. of stations) × commute time	.038***					
	(.010)					
ln(gasoline price) × PHEV	−.086	−.090	−.079	−.075	.037	−.093
	(.193)	(.200)	(.205)	(.204)	(.204)	(.245)
ln(gasoline price) × BEV	.389*	.411*	.424*	.440*	.292	.440*
	(.208)	(.217)	(.221)	(.218)	(.222)	(.256)
ln(retail price − tax incentives)	−1.324***	−1.294***	−1.214***	−1.300***		−1.499***
	(.130)	(.130)	(.147)	(.130)		(.150)
ln(residential charging from EV project)	.049***	.048***	.049***	.051***	.054***	.049***
	(.009)	(.012)	(.010)	(.009)	(.009)	(.010)
ln(personal income)	1.896***	1.710*	2.059**	2.026**	2.167**	2.849***
	(.708)	(.958)	(.868)	(.839)	(.859)	(1.040)
ln(hybrid sales in 2007) × time trend	.011***	.019	.011**	.012**	.011**	.009
	(.004)	(.024)	(.005)	(.005)	(.005)	(.006)

ln(personal income) × time trend	–.001	.044	.002	.003	–.004	–.020
	(.015)	(.081)	(.020)	(.019)	(.020)	(.027)
ln(hybrid sales in 2007) × time trend2		–.000				
		(.001)				
ln(personal income) × time trend2		–.003				
		(.005)				
ln(no. of stations) × battery EV			.094			
			(.059)			
College shares × time trend						–.023
						(.081)
Drive-to-work share × time trend						–.117
						(.116)
Use public transit to work × time trend						.071
						(.167)
White share × time trend						–.100**
						(.040)

Note. The dependent variable is ln(EV sales) by model by quarter. The number of observations for columns *a*–*e* is 14,563 and that for the last column is 11,614 due to missing values for the added controls in small MSAs. Column *d* adds two additional IVs, including tax credit for charging stations and a dummy for other state funding for charging stations. All specifications include year-quarter fixed effect, and MSA-model fixed effects. Standard errors are clustered at the MSA level.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

Table 6. Additional Specifications for Vehicle Demand, B

Variable	GMM (*g*)	GMM (*h*)	GMM (*i*)	GMM (*j*)	GMM (*k*)
ln(no. of charging stations)	.842***	.953***	1.005***	.725***	.683***
	(.162)	(.170)	(.281)	(.224)	(.347)
ln(gasoline price) × PHEV	−.083	.099		.127	.176
	(.206)	(.211)		(.204)	(.201)
ln(gasoline price) × BEV	.420*	.590**	.024	.238	.223
	(.220)	(.231)	(.283)	(.218)	(.220)
ln(retail price − tax incentives)	−1.288***	−1.283***	−.927***	−1.297***	−1.307***
	(.131)	(.131)	(.268)	(.135)	(.139)
ln(residential charging from EV project)	.050***	.049***	.027	.054***	.055***
	(.009)	(.011)	(.020)	(.012)	(.011)
ln(personal income)	2.058**	2.184**	.045	1.764**	2.900***
	(.854)	(.933)	(1.362)	(.831)	(.835)
ln(hybrid vehicle sales in 2007) × time trend	.011**	.006	.013	.014**	.015*
	(.005)	(.005)	(.008)	(.006)	(.008)
ln(personal income) × time trend	.001	−.001	.014	.008	.007
	(.020)	(.020)	(.032)	(.020)	(.020)
Observations	14,563	14,563	6,720	14,328	13,990

Note. Column *g* employs the logit model from Berry (1994) and the dependent variable is $\ln(s_{kit}) - \ln(s_{0mt})$, where s_{kmt} is the market share of model *k* in market *m* and time *t* and s_{0mt} is the share of consumers who are not purchasing an EV. Column *h* includes specific time fixed effects for ZEV states to control for a potential competition effect from the introduction of more EV models. Column *i* includes a sample of only BEV models. Columns *j* and *k* increase the lag of national number of charging stations to two and three quarters when constructing the instrumental variable. All specifications include year-quarter fixed effects, and MSA-model fixed effects. Standard errors are clustered at the MSA level.

* $p < .10$.
** $p < .05$.
*** $p < .01$.

4.3. Regression Results for Charging Station Deployment

Columns *a*–*d* in table 7 report the OLS regression results for the charging station equation (5) (first-stage results reported in table 8). In column *a*, only the four explanatory variables of interest are included. Column *b* includes year-quarter fixed effects to control for time trends that are common to all MSAs such as federal subsidies for building charging stations that occur during a specific period of time. Column *c* further includes MSA fixed effects to control for time-invariant MSA-level baseline differences

Table 7. Charging Station Equation

Variable	OLS (*a*)	OLS (*b*)	OLS (*c*)	OLS (*d*)	GMM (*e*)	GMM (*f*)
ln(EV installed base)	.374***	.540***	.136***	.115***	.613***	.659***
	(.025)	(.028)	(.029)	(.028)	(.157)	(.157)
Charging station tax credit (%)	−.005***	−.003*	.003	.003	.012	.012
	(.002)	(.002)	(.013)	(.014)	(.014)	(.014)
Public funding or grants	.099*	.077	.007	−.020	.078	.088
	(.060)	(.057)	(.048)	(.047)	(.054)	(.055)
ln(no. of grocery stores) × ln(lagged national stations)	.042***	.030***	.183***	.118***	.063**	.058**
	(.005)	(.005)	(.017)	(.020)	(.025)	(.025)
ln(hybrid vehicle sales in 2007) × time trend				.018***	.009**	.009*
				(.003)	(.004)	(.005)
Year-quarter fixed effects	No	Yes	Yes	Yes	Yes	Yes
MSA fixed effects	No	No	Yes	Yes	Yes	Yes
Overidentification test (p-value)					.3435	.1347
Underidentification test (p-value)					.0000	.0001

Note. The number of observations is 4,236. The dependent variable is ln(total number of publicly accessible charging stations) in an MSA in a quarter. Tax credit for charging stations is the state-level tax credit to cover the cost of installing charging stations and is measured in percentage. Public funding is a dummy variable indicating whether public grants for building charging stations are available. ln(no. of grocery stores) × ln(lagged national stations) is the instrumental variable used in the EV demand equation. Column *e* is the preferred specification with gasoline prices in previous years as the IV for ln(EV installed base). Column *f* adds tax incentives for EV purchases as an additional IV. All standard errors are clustered at the MSA level.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

in charging station investment. Column *d* adds in the interaction term between the hybrid vehicle sales in 2007 (proxy for environmental friendliness) and time trend to control for heterogeneity in the diffusion pattern of charging stations.

All OLS regressions find a positive and statistically significant coefficient for the installed EV base. The estimate results in column *d* suggest that a 10% increase in the EV fleet size would lead to a 1.2% increase in the number of public charging stations. The GMM results in column *e* show that a 10% increase in EV fleet size would result in a 6.1% increase in charging stations. In column *f*, we add the EV incentives

Table 8. First-Stage Results for Charging Station Equation

Variable	
ln(current gasoline price)	.206
	(.233)
ln(gasoline price last year)	3.304***
	(.824)
ln(gasoline price two years ago)	3.236***
	(.676)
ln(gasoline price three years ago)	3.087***
	(.810)
ln(hybrid vehicle sales in 2007) × time trend	.021***
	(.004)
ln(no. of grocery stores) × ln(national charging stations)	.085***
	(.023)
Charging station tax credit (%)	−.017
	(.018)
Public funding or grants for stations	−.228***
	(.061)
R^2	.922

Note. The number of observations is 4,236. The dependent variable is ln(EV stock). The model includes year-quarter fixed effects and MSA fixed effects. Standard errors (in parentheses) are clustered at the MSA level.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

(tax credits and rebates at the federal and state levels) as an additional instrument and the coefficient for charging stations increases from 0.613 to 0.659. We take column *e* as our baseline IV specification due to the concern that the EV incentives (especially those at the state level) could be endogenous as they could be a response to the unobserved shocks to the deployment of charging stations.

The GMM coefficient estimates are higher than all the OLS estimates, suggesting that the installed base of EVs is negatively related to the unobserved shocks to charging station investment, leading to downward bias in OLS. An example of the unobserved shocks is the unobserved local policies: policy makers may design policies to support charging station investment to counteract negative EV demand shocks.

The results in column *e* show that tax credits and the availability of public funding for charging stations have positive but statistically insignificant coefficients. The tax credits and public funding are both at the state level. The dependent variable in the charging station equation, however, only includes publicly accessible charging stations, which are mainly subsidized by the federal government directly through federal projects such as the EV Project and ChargePoint Project. Although state-level tax credits and funding also apply to public charging stations, they mostly support the installation of charging stations at workplace and multifamily dwellings, which are usually privately accessible and are excluded from our analysis. The interaction term of grocery stores with the lagged number of stations in all MSAs other than own has a positive and statistically significant coefficient, consistent with our argument for using it as a relevant instrument in the EV demand equation.

5. POLICY SIMULATIONS

Our empirical analysis suggests that indirect network effects exist on both sides of the market. In this section, we first examine the policy impact of the current federal income tax credit policy for EV buyers and then compare this policy with an alternative policy that subsidizes charging station investment instead.

5.1. 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 CBO (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.[26] The credit will expire once 200,000 qualified EVs have been sold by each manufacturer.

In order to examine the effectiveness of the income tax credit policy in terms of stimulating EV sales, we use our parameters estimates from the two baseline GMM regressions to stimulate the counterfactual sales of EVs that would arise in the absence of the $924.2 million worth of tax credits to EV buyers from 2011 to 2013. The impact of the policy depends not only on the price elasticity of EV demand in the EV demand equation but also on the magnitude of indirect network effects captured in both equations.

We assume in our simulations that the MSRPs will not be affected, implying that consumers previously captured all the subsidies. We believe that this is a reasonable assumption in the EV launch stage when automakers produce EVs likely at a loss

26. The only EV models that are not eligible for the full amount of credits are Honda Accord Plug-in, Ford C-Max Energi, Porsche Panamera, and Toyota Prius plug-in. And their eligible tax credits are $3,626, $4,007, $4,751.8, and $2,500, respectively. In our policy simulation, we remove the tax credits based on different models.

since the production level is far below the efficient production scale.[27] While more and more states are providing subsidy programs to encourage the adoption of EVs, the retail prices for electric vehicles have actually been decreasing (for the same model) during our sample period likely due to decreasing production cost and the increasing competition.

Our simulation results in table 9 show that EV sales would have been 56,690 less (or 40.44% of the total sales) from 2011 to 2013 without the $924.2 million worth of income tax credit to EV buyers. If we shut down feedback loops, the sales contribution from the tax credit policy would only have been 33,949 (24.2% of the total sales). This implies that feedback loops magnify the policy shock and explain 40% of the sales increase from the policy. The results suggest that feedback loops have a multiplier effect of 1.67. The CBO finds the policy impact to be 30% of the total EV sales while their study only considers the price effect of the tax credit but not the role of indirect network effects in amplifying the policy effect (CBO 2012). DeShazo et al. (2014) study the California Clean Vehicle Rebate Projects for EVs and find a 7% increase in EV sales from the rebate of $1,838 on average. Neither of these studies takes into account indirect network effects, and their estimates likely provide the lower bounds of subsidy impacts.

5.2. Policy Comparison

Our stylized model suggests that feedback loops from indirect network effects on both sides of the market have important policy implications. A policy shock on one side of the market would affect the other side. To promote EV adoption based on a variety of rationales as discussed in section 1.2, policy makers face a problem of optimal policy design in that the tax revenue can be used to subsidize one or both sides of the market. We compare the subsidy policy on EV purchase with an alternative policy of subsidizing charging station investment. The alternative policy uses the same budget of $924.2 million evenly in each quarter during 2011–13 to install charging stations in all MSAs (proportional to population). As a lower bound estimate of the investment cost of charging stations, we assume the government is only responsible for the purchase and installation of the charging hardware and the charging station company will then operate and maintain the charging stations, as in the case of the EV Project and ChargePoint Project, the two federal charging station support programs. As a robustness check, we also estimate an upper bound investment cost for charging stations assuming the government will also need to maintain and operate those charging stations.

27. In a study by Sallee (2011) on the income tax credit on hybrid vehicles after hybrid vehicles were first introduced to the market, he finds that consumers captured the majority of the gains for the income tax subsidy. Automobile assembly lines generally operate most efficiently with an output of 200,000–250,000 vehicles per platform (Rubenstein 2002). The global sales of the most popular EV model, Nissan Leaf, was only 61,027 in 2014.

Table 9. Policy Impacts of Federal Income Tax Credits for EVs

Time	Observed EV Sales	Counterfactual Sales	Sales Reduction	Percentage
2011–1	1,105	772	333	30.10%
2011–2	3,241	2,580	661	20.40%
2011–3	2,813	1,887	926	32.91%
2011–4	3,900	2,256	1,644	42.16%
2012–1	4,307	2,015	2,292	53.22%
2012–2	7,030	3,517	3,513	49.97%
2012–3	9,662	5,575	4,087	42.30%
2012–4	12,665	7,838	4,827	38.11%
2013–1	21,140	12,931	8,209	38.83%
2013–2	24,803	15,571	9,232	37.22%
2013–3	25,782	15,679	10,103	39.19%
2013–4	23,747	12,884	10,863	45.74%
Total	140,195	83,505	56,690	40.44%

Note. Counterfactual sales are the simulated sales in all 353 MSAs in our data after removing the federal income tax credit for EV buyers (the amount based on different models) while holding everything else the same.

The lower bound and the upper bound of the charging station investment cost are $27,000 and $50,244, respectively.[28]

The policy comparison between these two policies is provided in table 10. We assume the policy period runs from 2011 to 2013 (i.e., no subsidy available in either policy after that). The existing tax credit policy (policy 1) has led to 56,690 more EVs from 2011 to 2013, amounting to $16,303 for one additional EV. The policy effect will continue to exist until the feedback loops die out in 2055.[29] The impact on EV sales from this policy in the long term would be 184,049, amounting to

28. According to the charging station cost report by US Department of Energy Vehicle Technologies Office (2015), the maintenance and operation cost of charging stations include the following components: electricity use, network fee, maintenance and repair, and rents in parking lots. The average electricity consumption is reported to be 6,864 kWh per year with an average network fee of $500 and maintenance fee of $300. Assuming the charging station charges customers $0.39 per kWh (the current charging fee of Blink Network supported by the EV project) and the average annual parking lot rate being $1,995.12 (the national average parking lot rate in 2012 Colliers International Parking Rate Survey), the estimated operation and maintenance cost less revenue is $805 per charging unit and $2,896 per station (3.6 units per station). Assuming a 10-year life span of a charging station, the discounted total cost of maintenance and operation is $23,244 per station and the total investment cost of a charging station including initial installation is $50,244.

29. We assume that the public charging stations and the installed base of EV drivers keep increasing at a rate that was observed in the last quarter of 2013.

Table 10. Comparison of EV Income Tax Credit and Charging Station Subsidy Policies

	EV Sales Increase from Policy 1	EV Sales Increase from Policy 2	
		Low Cost	High Cost
2011–1	333	2,532	1,439
2011–2	661	3,839	2,214
2011–3	926	4,116	2,422
2011–4	1,644	5,937	3,505
2012–1	2,292	6,500	3,891
2012–2	3,513	8,599	5,185
2012–3	4,087	9,074	5,482
2012–4	4,827	9,856	5,966
2013–1	8,209	17,832	10,762
2013–2	9,232	18,340	11,088
2013–3	10,103	18,880	11,443
2013–4	10,863	19,397	11,801
Sales increase in 3 years	56,690	124,904	75,199
Total increase long-term	184,049	403,558	267,741
Total increase in 10 years	168,131	373,748	245,687
Government spending per EV	\$5,022	\$2,290	\$3,452

Note. Both policies use \$924.2 million. Policy 1 provides a rebate in the form of tax credits for EV buyers with the amount the same as the current income tax credit policy for each EV model. Policy 2 uses the same budget to build charging stations evenly in each quarter in all metro areas weighted by population. We assume investing a charging station has a lower-bound cost of \$27,000 and an upper-bound cost of \$50,244. Total increase includes vehicle sales increase during the policy effective period and the increase in future years (until 2055) discounted to year 2011 by a 5% discount rate.

\$5,022 per policy-induced EV purchase. If instead, the government had spent the \$924.2 million subsidizing charging stations by purchasing and installing charging infrastructure (policy 2 with lower station cost), EV sales would have increased by 124,904 during these 3 years. The cumulative impact on EV sales from this policy until year 2055 would be 403,558, amounting to \$2,290 per induced EV, only 46% of the unit cost under the existing policy. If the government were also responsible for maintaining and operating those stations (policy 2 with higher station cost), EV sales would have increased by 75,199 during these three years and 267,741 in the long term, amounting to \$3,452 per induced EV, still preferable to policy 1.

As depicted in figure 6, policy 2, which subsidizes charging station investment, demonstrates a dominant advantage in stimulating EV sales in the early stage of the EV market. The \$924.2 million spending during the 3 years can install about 18,395 to 34,231

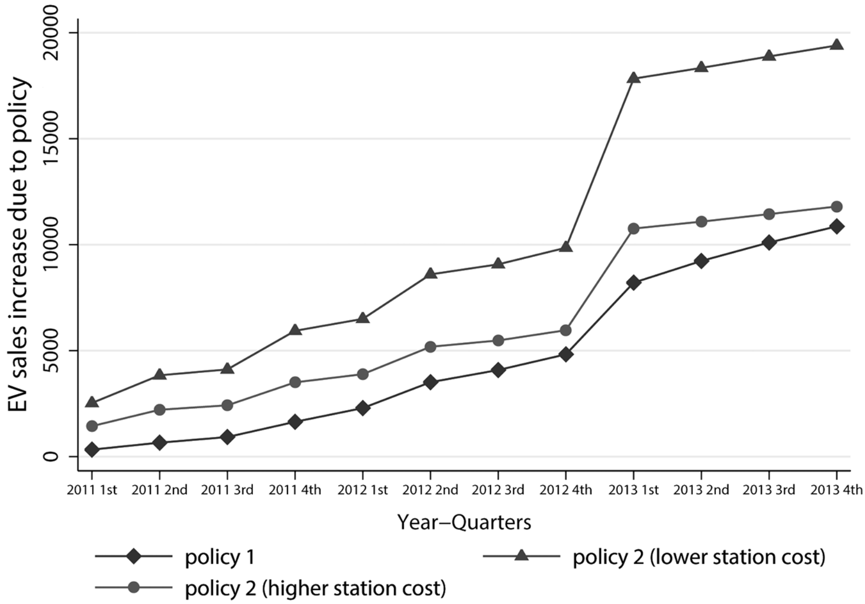

Figure 6. Sales impacts from two subsidy policies. Each data point represents EV sales increase by quarter due to the policy. Policy 1 gives new EV buyers a tax credit of $2,500–$7,500 based on different models as the current income tax credit policy for EVs. Policy 2 builds charging stations in all MSAs with the same total spending as policy 1 by assuming a charging station investment cost with a lower bound cost of $27,000 and an upper bound of $50,244.

charging stations depending on the actual investment cost. This is more than one-eighth to one-fourth of the total number of gasoline stations in the country and almost one and half to three times of the current total number of public charging stations in the whole country. This large amount of public charging stations should dramatically alleviate or even eliminate range anxiety for potential EV buyers. Our results indicate that building charging stations is a more effective way to boost EV sales in the EV launch stage. As shown in our regression results, indirect network effects on the EV demand side are much stronger than those on the charging station side (coefficient ratio being 1.4) and consumers are not very sensitive to prices (price elasticity being −1.3). As a result, the policy that builds charging stations stimulates EV sales at a much faster pace, consistent with our findings in the model section.

The long-run simulations are based on a variety of assumptions and are meant to be illustrative. As the technology improves, the EV driving range is likely to increase, weakening indirect network effects from charging stations to EV demand. In addition, in the longer term, as EVs become more of a serious choice for average vehicle buyers, consumer price sensitivity among EV buyers could increase. Both of these changes would affect the policy outcomes and weaken the effectiveness of policy 2 relative to policy 1.

As discussed in section 4.2, the network size of charging stations has heterogeneous impacts on the EV demand across locations with different average commute time. This implies heterogeneity in the relative strength of indirect network effects on the two sides of the EV market and hence heterogeneity in policy comparison. That is, policy 2 may not be always preferred as previous analysis suggests. In MSAs where indirect network effects on EV demand are not strong since drivers have shorter commutes and home charging is enough to ensure their daily trips, policy 1, which subsidies EV purchase, could be more effective. Figure 7 depicts the relative effectiveness of the two policies in promoting EV adoption. The MSA with policy 2 being most effective is New York–New Jersey–Long Island (NY-NJ-PA) where the average commute time is longest, while the MSA with policy 1 being most effective is Grand Forks (ND-MN) where the average commute time is shortest. This suggests that a more elaborate and cost-effective policy design would be to subsidize charging stations in areas with long commute (e.g., large MSAs) but to subsidize EV purchases in areas with short commute (e.g., small MSAs). This type of regionally differentiated policy could be implemented at the federal level but perhaps more feasibly at the state and local levels. For example, in states or cities where the average commute is longer, state and local governments should focus on building charging station infrastructure while subsidies on EV adoption, for example, through rebate and HOV lane usage, can be implemented in states and cities where the average commute is shorter.

6. CONCLUSION

This study first demonstrates through a stylized model that positive indirect network effects in both EV demand and charging station deployment give rise to feedback loops that amplify shocks to the system and have important policy implications. Although indirect network effects on both sides of the market imply that subsidizing either side of the market will result in an increase in both EV sales and charging stations, the relative cost effectiveness of different subsidy policies depends on consumer price sensitivity for EVs and the relative magnitude of indirect network effects on the two sides of the market.

The paper provides to our knowledge the first empirical analysis of indirect network effects in this market and evaluates the impacts of the current federal income tax credit program for EV buyers. Our analysis estimates the elasticity of EV adoption with respect to charging station availability to be 0.84 and the elasticity of charging station investment with respect to the EV installed base to be 0.61. These indirect network effects enhance the effectiveness of the tax credit policy, which has contributed to 40% of EV sales during 2011–13 and will continue to exhibit a positive effect on the market for many years through feedback loops. Given the relative strength of indirect network effects on the EV demand side and the low price sensitivity of early adopters, subsidizing charging station deployment would be much more cost effective than the current policy of subsidizing EV purchases.

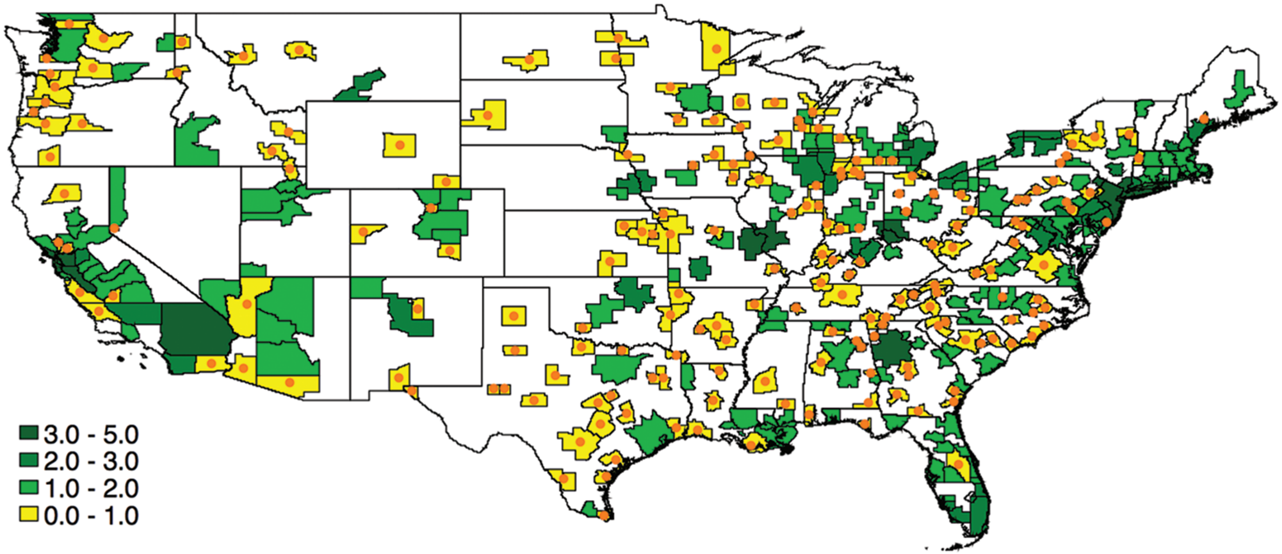

Figure 7. Heterogeneous policy effectiveness (policy2/policy1). Policy 1 gives new EV buyers a tax credit of \$2,500–\$7,500 based on different models as the current income tax credit policy for EVs. Policy 2 builds charging stations in all MSAs with the same budgetary cost as policy 1, assuming the investment cost per station being \$27,000. The figure plots the ratio of the EV increases due to the two subsidy policies. The policy effectiveness of policy 2 varies across locations due to the heterogeneous impacts of public charging stations on the EV demand. The regions with the dots are locations where policy 1 is more effective.

Our findings offer some insights for policy design to promote EV technology. First, the policy to expand the charging station network (e.g., through subsidies) would be especially effective in the EV launch stage due to the low price sensitivity of early adopters and strong indirect network effects from charging stations on EV demand. Second, our analysis demonstrates that significant spatial differences exist in optimal policy design. Together with the finding from the literature that the environmental benefits from EVs exhibit significant heterogeneity across locations with a different fuel mix of electricity generation, the spatial variation in indirect network effects limits one-size-fits-all policies and argues for regionally differentiated policies.

APPENDIX

ENTRY MODEL OF CHARGING STATIONS

The entry model is developed based on Gandal et al. (2000). Denote EV owners' demand for charging station j by $D(p_1, \ldots, p_N)$, where N is the number of charging stations available in a given market, and p_j is the price at charging station j, $j = 1, \ldots, N$. We assume that demands are symmetric in terms of prices at different charging stations. Furthermore, we assume that the marginal cost is constant, denoted by c, and that the profit function from each EV owner $(p_j - c)D(p_1, \ldots, p_N)$ is quasi-concave in p_j. Under these assumptions, there exists an equilibrium in which all stations charge the same price, which depends on N, denoted by $p(N)$. Denote the equilibrium markup by

$$\varphi(N)\left(\equiv -\frac{D(p)}{\left[\frac{\partial D(p)}{\partial p}\right]}\right)$$

and assume $\varphi'(N) < 0$, which is consistent with most common competition models. Let $f(N) = \varphi(N)D\,(p(N))/N$. Then the per period profit of a station in market m at time t is $\pi_{mt} = Q_{mt}^{EV}f(N_{mt})$.

Now consider a charging station's entry decision. If a charging station enters market m at time t, it pays the entry cost F_{mt} and earns the profit streams $(\pi_{mt}, \pi_{(mt+1)}\ldots)$, generating a discounted profit of $-F_{mt} + \pi_{mt} + \delta\pi_{mt+1} + \ldots$, where δ is a discount factor common to all stations. If a station enters market m at time $t + 1$, it generates a discounted profit of $-\delta F_{mt+1} + \delta\pi_{mt+1} + \delta^2\pi_{mt+2}\ldots$. In a free-entry equilibrium firms must be indifferent between these two options. This implies

$$F_{mt} - \delta F_{mt+1} = \pi_{mt} = Q_{mt}^{EV}f(N_{mt}).$$

Taking the natural logarithms of both sides, we can get

$$\ln(F_{mt} - \delta F_{mt+1}) = \ln(f(N_{mt})) + \ln(Q_{mt}^{EV}). \tag{A1}$$

We specify the entry cost as

$$\ln(F_{mt} - \delta F_{mt+1}) = \rho_0 + \rho_1 Z_{mt} + \tau_{mt}, \tag{A2}$$

where τ_{mt} is the unobserved entry cost, and the vector of covariates Z_{mt} includes the state-level tax credit given to charging station investors measured as the percentage of the building cost, a dummy variable indicating whether there exists public grants or funding to building charging infrastructure, the interaction term of number of grocery stores in an MSA in 2012 with the lagged number of charging stations in all MSAs other than own (the instrument in the EV demand equation), and other control variables.

We specify the profitability of charging station $f(N)$ as follows

$$\ln(f(N_{mt})) = \lambda_0 + \lambda_1 \ln(Q^{EV}_{mt}) + \vartheta_{mt}, \tag{A3}$$

where N_{mt} is installed base of charging stations by time t which captures the competition among charging stations, and ϑ_{mt} is an error term that captures the unobserved local demand shocks.

Furthermore, we decompose the local shock as

$$(\tau_{mt} - \vartheta_{mt})/\lambda_1 = T_t + \varphi_m + \varsigma_{mt}, \tag{A4}$$

where T_t is year-quarter dummies that control for time effects common to all the MSAs, φ_m is market fixed effects that control for time-invariant and MSA-specific preferences for charging stations, and ς_{mt} is an term capturing those idiosyncratic local demand shocks.

From equations (A1), (A2), (A3), and (A4), we can obtain the charging station equation (5) in section 3.2:

$$\ln(N_{mt}) = \gamma_0 + \gamma_1 \ln(Q^{EV}_{mt}) + \gamma_2 Z_{mt} + T_t + \varphi_m + \varsigma_{mt},$$

where $\gamma_0 = (\rho_0 - \lambda_0)/\lambda_1, \gamma_1 = -1/\lambda_1, \gamma_2 = \rho_1/\lambda_1$.

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