THE MARKET FOR ELECTRIC VEHICLES: INDIRECT NETWORK EFFECTS AND POLICY IMPACTS

A Thesis

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by

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ABSTRACT

Plug-in electric vehicles (EVs) offer great potential in reducing local air pollution and carbon emissions and in alleviating dependency on fossil fuel. However, there are significant barriers to the diffusion process of this new technology. The EV market features indirect network effects (or the chicken-and-egg problem) in that consumers may be reluctant to adopt EVs with the lack of public charging stations while investors are less willing to build charging stations when the installed base of EVs is small. Indirect network effects could amplify shocks whether negative or positive through feedback loops and therefore could slow down or speed up the diffusion process. Using a data set of quarterly EV sales in 353 metro areas from 2011 to 2013, this paper provides the first empirical analysis on the importance of indirect network effects in this market: a 10% increase in the number of charging stations would increase the EV sales by 10.8% while a 10% growth in the EV stock would lead to a 5.8% increase in the number of charging stations. Our simulation results find that the current federal tax credits of up to $7,500 have contributed to 48.5% of the EV sales during 2011-2013, with indirect network effect explaining 42% of that sales increase. The total tax credit of $1.05 billion given out during these three years brought about $0.23 billion in long-term environmental benefits, while a policy of equal-size spending but subsidizing charging station building would be several times more effective.

BIOGRAPHICAL SKETCH

Jianwei Xing was born in Nantong, Jiangsu Province, P. R. China on Nov. 25th, 1988. He participated in Sino-American 1+2+1 Dual Degree Program in 2008 and graduated from both Nanjing University of Information Science & Technology and George Mason University with a Bachelor of Science Degree in Economics. During his undergraduate study at George Mason University, he was on Dean's List every semester and won Howard R. Block Memorial Award and The Economics Department Award for Outstanding Academic Achievement.

In 2011, Jianwei was admitted by Master of Science program in the Dyson School of Applied Economics and Management at Cornell University. During the first year of graduate-level study, he found his research interest in environmental and energy economics with a focus on transportation related topics. He conducted some research projects with Professor Shanjun Li, including an IMF project that estimates the marginal congestion cost in different countries and a NSF project examining the interplay of electric vehicle sales and the charging infrastructure deployment. Because of his excellent performance, he was admitted to the PhD program at Dyson School and will continue his research in environmental economics.

This is dedicated to my family and friends.

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CHAPTER 1: INTRODUCTION

The U.S. transportation sector contributes to nearly 30% of total U.S. greenhouse gas emissions, over half of total carbon monoxide and nitrogen oxides emissions, and about a quarter of total hydrocarbons emissions in recent years. It also accounts for about three-quarters of U.S. petroleum consumption. Plug-in electric vehicles (EVs) offer great potential in reducing air pollution and strengthening energy security. EVs can be recharged from an external source of electricity and the electricity stored in the rechargeable battery packs drives the wheels. 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 or diesel) to power a combustion engine (e.g., Chevrolet Volt). BEVs and PHEVs, if operated under all-electric mode, produce zero tailpipe emissions. The electricity used in EVs is produced from domestic coal, natural gas, nuclear and other renewable energies. The environmental benefit could be especially large if the electricity comes from renewable sources.

The mass-market EVs were (re-)introduced into the U.S. market in late 2010.[1] The monthly sales of EVs have increased from 345 in December 2010 to 9,790 in December 2013 (source: Hybridcars.com and Baum & Associates) (Figure 1.1). The sales have been concentrated in large urban centers (Panel (a) in Figure 1.2). Despite

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

the rapid growth, the market share of electric cars is still relatively small: the total EV sales only made up 0.62% of the total new vehicle sales in 2013 (source: Hybridcars.com and Baum & Associates). In the 2011 State of the Union address, President Obama set up a goal of one million EVs by 2015 and based on the market development so far, the goal is unlikely to be achieved. As a new technology, EVs face several significant barriers to wider adoption including the high purchase cost, limited driving range and long charging time, and the lack of charging infrastructure.

EVs are more expensive than their conventional gasoline vehicle counterparts. The manufacturer's suggested retail prices (MSRP) for the 2014 model of Nissan Leaf and Chevrolet Volt are $28,980 and $34,185, respectively, while the average price for a comparable conventional vehicle (e.g., Nissan Sentra, Chevrolet Cruze, Ford Focus and Honda Civic) is between $16,000 and $18,000. To reduce the price gap between EVs and their gasoline counterparts, the Energy Improvement and Extension Act of 2008, and later the American Clean Energy and Security Act of 2009 grant tax credit for new qualified EVs. The minimum credit is $2,500 and the credit may be up to $7,500, based on each vehicle's battery capacity and the gross vehicle weight rating. Moreover, several states have established additional state-level incentives to further promote EV adoption such as tax exemptions and rebates for EVs and non-monetary incentives such as HOV lane access, toll reduction and free parking.

The other notable barrier of EV adoption is consumers' concerns over the driving range and charging time. BEVs have a shorter range per charge than conventional vehicles have per tank of gas, contributing to consumer anxiety of running out of electricity before reaching a charging station. Auto manufacturers usually target a range of 100 miles on a fully charged battery. Nissan LEAF, the most popular BEV in the U.S. has an EPA-rated range of 84 miles on a fully charged battery in 2014. Chevrolet Volt has an all-electric range of 38 miles, beyond which it will operate under gasoline mode. This range is sufficient for daily household vehicle trips but may not be enough for longer distance travels. In addition, it takes much longer to charge EVs than to fill up gasoline vehicles. A BEV may not be able to get fully charged overnight if just using a regular 120 Volt electric plug (it takes 21 hours for Nissan LEAF to get fully charged) (source: Hybridcars.com 2014 Nissan Leaf Overview). To get faster charging, BEV drivers either need to install a charging station at home or go to public charging stations. Unlike BEVs, PHEV batteries can be charged not only by an outside electric 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 an EV.

Given the limited battery capacity and driving range, consumers are reluctant to adopt EVs if the availability of public charging stations are scarce. Despite the rapid growth in the last few years, there are only less than 9,000 public charging stations in the U.S. (Figure 1.1), compared to over 120,000 gasoline stations. The diffusion of EVs should benefit from a wider distribution of charging infrastructure, which would reduce range anxiety and allow PHEVs to operate more under the all-electric mode to save gasoline. The Department of Energy and some state governments have provided significant funding to expand the network of charging stations to address this concern.

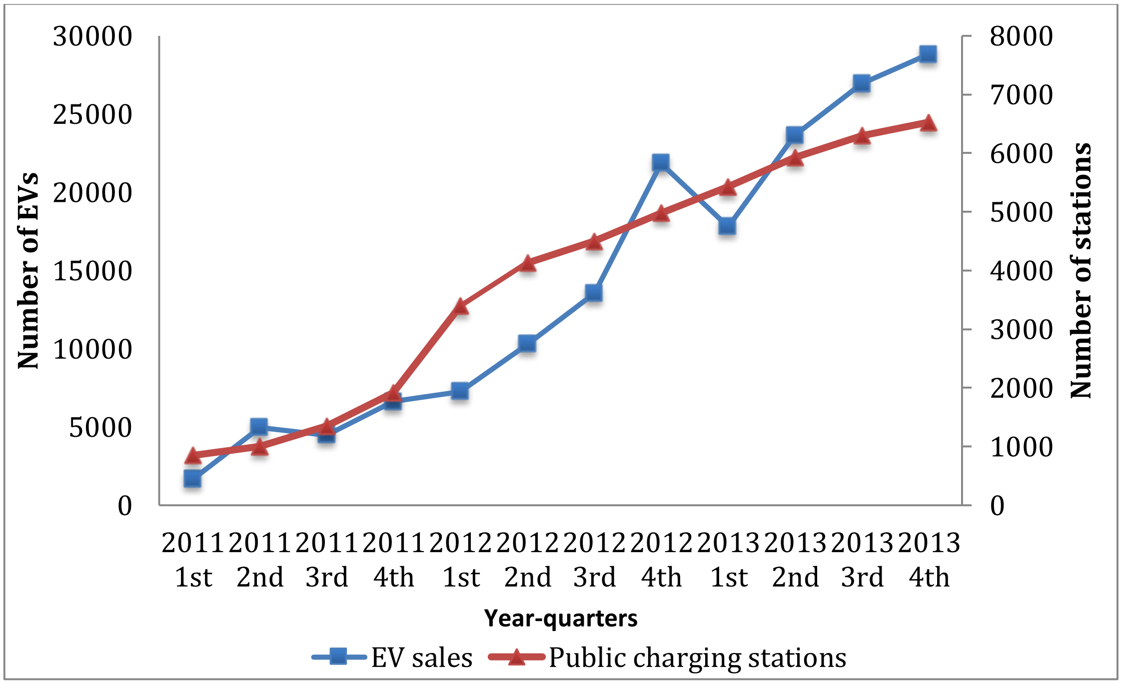
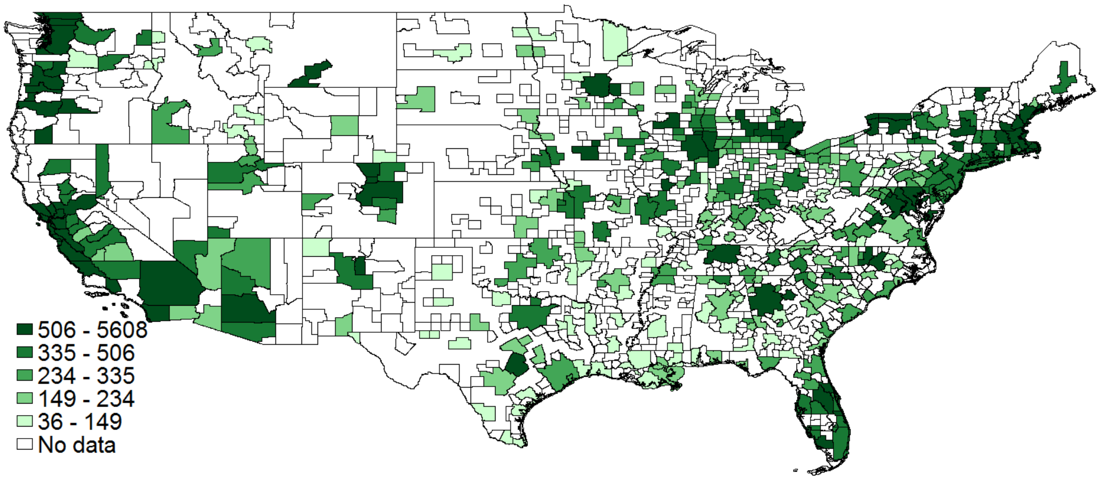


Figure 1.1 National EV sales and public charging stations

Nevertheless, private investors have less incentive to build charging stations if the size of the EV fleet and the market potential are small. The inter-dependence between the two sides of the market (EVs and charging stations) can be characterized as indirect network effects: the benefit of adoption/investment on one side of the market increases with the network size of the other side of the market. The inter-dependence could partly explain the similarity in the spatial pattern of EV stock and charging stations depicted in Panels (a) and (b) in Figure 1.2. While indirect network effects could exacerbate the negative impacts of the barriers on any side of the market (such as the high purchase cost) and slow down the diffusion problem, they could also amplify the positive shocks through feedback loops and hence speed up the diffusion.

Panel (a) Installed base of EVs per million people



Panel (b) Public charging stations per million people

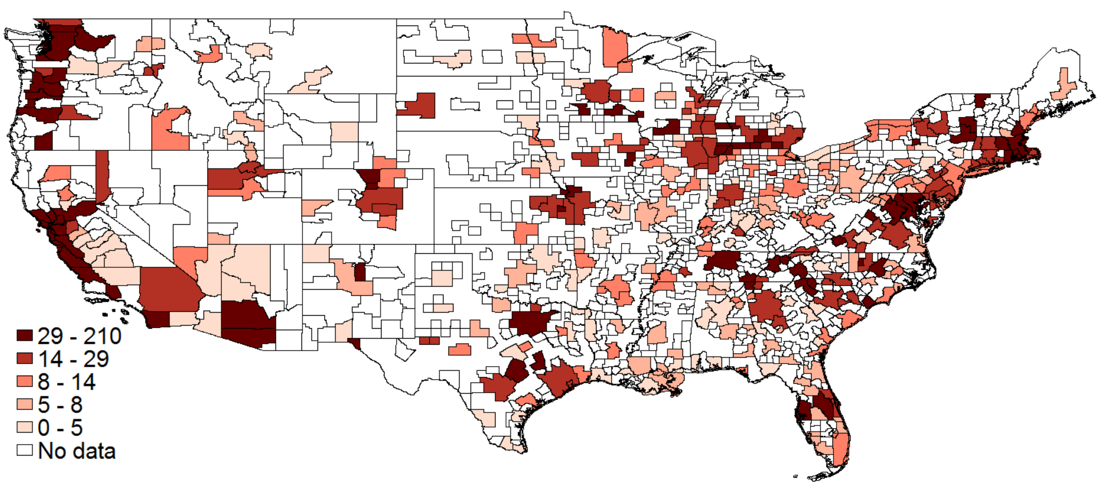


Figure 1.2 Spatial distributions of EVs and public charging stations
Source: HIS Automotive and DOE Alternative Fuel Data Center (4th quarter of 2013)

The main purpose of this study is to: (1) use econometric methods and real-world data to quantify indirect network effects in the EV market, and (2) evaluate the effectiveness of the current federal tax credit policy as well as alternative policy designs.

Our empirical analysis confirms that consumer adoption would benefit from a larger network of charging stations and that a larger installed base of EVs would lead to more investment in charging infrastructure. The federal tax credit policy has been an important driver behind consumer adoption of EVs. Nevertheless, model simulations show that the effectiveness of government spending could have been greatly enhanced if the funding had been used to build charging stations instead due to strong indirect network effects.

CHAPTER 2: LITERATURE REVIEW

Our study is related to previous work on indirect network effects that dates back to early theoretic papers such as Rohlfs (1974), Katz and Shapiro (1985) and Farrell and Saloner (1985). Empirical study on indirect network effects has been seen in recent industrial organization literature, much of which focuses on the markets that can be characterized by classic software and hardware paradigm, including Gandal, Kende, and Rob (2010)'s study of CD titles and CD players, and Nair, Chintagunta, and Dube (2003)'s study of PDAs and compatible software. Many studies analyze the indirect network effects in the video game industry and assess the importance of the network effects in the game system competition including Clements and Ohashi (2005) and Corts and Lederman (2009) who investigate the indirect network effects in the U.S. video game market. These two studies both use static formulation to estimate the hardware demand and software supply sides and employ instrumental variable estimation to solve the endogeneity issue. Dube, Hitsh, and Chintagunta (2010) develop a dynamic model that captures the indirect network effects in a hardware and software market to measure the increases in a firm's market share dominance caused by indirect network effects. Lee (2013) estimates a dynamic model of both consumer demand for hardware and software products, and software company demand for hardware platforms to measure the impact of vertically integrated and exclusive software on industry structure and competition in the U.S. video game market between 2000 and 2005. Zhou (2013) develops a dynamic structural model of the video game market to study the launch failure of a game system and shows that a failed platform could have survived if it had priced properly during its launch stage.

The indirect network effects have also been studied in markets that are not usually characterized by canonical hardware and software paradigm such as Rysman's study of network effects in the market for Yellow Pages directories (2004) and payment cards (2007). Corts (2010) extends the study of network effects to the clean fuel vehicle industry by examining the effect of the installed base of FFVs on E85 availability especially the impact of government fleet adoption of FFVs, but his study estimates only one side of the network effects due to data constraint.

Our study contributes to the literature by providing a first step empirical analysis of the indirect network effects existing in the electric vehicle industry. Our study focuses on the static formulation by estimating both the consumer vehicle adoption and the charging station supply sides separately and using instrumental variable method to deal with the endogeneity concern.

CHAPTER 3: METHODOLOGY

3.1 Data

Our sample includes 353 Metropolitan Statistical Areas (MSAs) and the study period is 2011-2013. The EV sales in these 353 MSAs account for 83% of the national EV sales. 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. Data on quarterly vehicle sales of each EV model in each MSA is purchased from IHS Automotive. We select the 353 MSAs for which observations are available in all three years. Data on the number of publicly accessible charging stations is collected from the Alternative Fuel Data Center (AFDC) of the Department of Energy. By matching the ZIP code of each charging station to an MSA and using the station open date (which was provided in the off-line version of their data base), we obtain the data set of the total number of public charging stations available in each quarter for each MSA. Data of all state-level incentive policies for both electric vehicles and charging stations are also collected from AFDC. Only monetary incentives such as tax credits and rebates are included in our analysis. Table 3.1 presents summary statistics of the variables used in our regression analysis.

Table 3.1 Data Summary Statistics

Variables	Mean	Std.dev
Panel (a): vehicle demand equation		
Log (sales of a EV model)	1.13	1.22
Log (gasoline prices)	1.26	0.07
Log (retail price-tax incentives)	10.30	0.43
Log (No. of charging stations)	1.91	1.47
Log(No. of stores)*log(nation stations)	39.01	10.39
Log(EV Project)	0.19	0.97
Number of observations	14626	
Panel (b): Charging station equation		
Log (No. of charging stations)	1.25	1.25
Log (No. of EV installed base)	2.82	1.89
Current gasoline prices	3.49	0.27
Gasoline price last year	3.25	0.39
Gasoline price two years ago	2.78	0.59
Gasoline price three years ago	2.78	0.58
Charging station tax credit (%)	4.54	14.70
Public funding or grants	0.33	0.47
Log(No. of stores)*log(nation stations)	34.57	9.29
Number of observations	4236	

3.2 EV Demand Regression

Using a panel dataset of quarterly EV sales by vehicle model and the number of charging stations for 353 Metropolitan Statistical Areas (MSAs) from 2011 to 2013, we conduct regression analysis to empirically quantify the relationship between the availability of charging stations and EV sales. 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:

$$(1)\ \ln(q_{kmt} + 1) = \beta_0 + \beta_1 ln(N_{mt} + 1) + \beta_2 \ln(MSRP_{kt} - d_{kmt}) + \beta_3 \ln Pgas_{mt} + \beta_4 \ln(EVP_{mt} + 1) + T_t + \delta_k + \varphi_m + \varepsilon_{kmt}$$

where q_{kmt} is the sales a EV model k in market m and year-quarter t. N_{mt} denotes the total number of public charging stations that have been built in the MSA by the end of a given quarter. 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 chargers. $ln(N_{mt} + 1)$ captures the effect of charging stations on electric vehicle purchases and the log form allows the incremental effect of charging stations to taper off in a MSA with a large number of stations. The addition of 1 in $ln(N_{mt} + 1)$ is used to include markets that do not have any charging stations built by quarter t and our results are robust to excluding these markets and using $ln(N_{mt})$ instead. The price effect is captured by $\ln(MSRP_{kt} - d_{kmt})$ where $MSRP_{kt}$ is the manufacturer's suggested retail price of a model and d_{kmt} denotes subsidies (tax credits and tax rebates at both federal and state levels) for purchasing the vehicle model. $\ln Pgas_{mt}$ captures the effect of quarterly gasoline prices. $\ln(EVP_{mt} + 1)$ denotes the log number of residential charging stations built by the EV Project[2]. Year-quarter fixed effects T_t control for time effects for electric vehicle purchases that are common to all the markets, e.g., a national demand shock for all EVs. Vehicle model fixed effects δ_k control for time-invariant product attributes associated with a specific vehicle model that affect consumer preference, such as comfort and

[2] The EV Project, is managed by ECOtality North America and supported by the U.S. Department of Energy with a total budget of over $230 million to deploy level-2 residential and commercial charging stations in the U.S.

brand loyalty. Market fixed effects φ_m control for time-invariant MSA specific preference for EVs such as stronger environmental awareness. 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).

Although we include a rich set of control variables, the charging station variable could still be endogenous due to simultaneity: EV purchases and charging station investment decisions in the current period are simultaneously determined. The time-varying and market-specific demand shocks that we do not observe would also affect charging station investment decisions. In this case, we cannot interpret the coefficient estimate on the charging station variable as the causal effect.

To deal with the endogeneity concern, we employ an IV strategy for estimation and a valid instrument 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 error term). We use as an IV the interaction term of the number of grocery stores and supermarkets in an MSA with the number of charging stations in all MSAs lagged for one quarter. Grocery stores and supermarkets could be good sites for public charging stations because EV drivers can charge their vehicles while shopping and these sites could also be good for publicizing EVs. Nissan is playing an active role in placing charging stations in popular grocery store locations. Kroger, the country's largest grocery store owner, has partnered with ECOtality Inc. to install about 300 charging stations in their store locations across the country. Our data shows that the number of grocery stores in an MSA is positively correlated with the number of charging stations.

However, the number of grocery stores does not vary with time in our sample period and it is therefore absorbed by the MSA fixed effects. To introduce temporal variation, we multiply it with the lagged number of charging stations that have been built in all MSAs in each quarter, which captures the national-level trend in charging station investments due to aggregate shocks such as cost changes over time and federal incentive programs. As shown in the first-stage results in Table 4.2, these shocks have larger impacts on charging station investments in areas with more potential good sites such as grocery stores and supermarkets. In addition, this instrument should satisfy the exclusion condition because the number of grocery stores and supermarkets is unlikely to directly affect EV sales. The lagged number of charging stations in all MSAs is pre-determined to the current period and is unlikely to be correlated with the unobserved shocks to the current sales of a specific EV brand in an MSA.

3.3 Charging Stations Regression

We specify the number of public charging stations available in each MSA in each quarter as a function of the installed base of EVs (new and old), state-level tax credits for charging stations (measured in percentage of the cost) and other control variables, while controlling for time fixed effects and MSA fixed effects. The empirical model of new charging station investment is described by the following equation:

$$(2)\ \ln(N_{mt}+1)=\gamma_0+\gamma_1\ln(Q_{mt}^{EV}+1)+\gamma_2 TC_{mt}+\gamma_3(lnG_m * lnTN_{t-1})+\gamma_4 f_{mt} +T_t+\varphi_m+\varsigma_{mt},$$

where N_{mt}denotes the total number of public charging stations that have been built in market m by quarter t and Q_{mt}^{EV} denotes the installed base of EVs by the end of year-quarter t. The addition of 1 in $\ln(N_{mt}+1)$ and $\ln(Q_{mt}^{EV}+1)$ is performed in order to include markets that do not have any new charging stations built or any electric vehicles purchased by quarter t. In this station supply equation, the effect of installed EV base on charging station investment is captured by $\ln(Q_{mt}^{EV}+1)$. TC_{mt} denotes the tax credit given to charging station investors and it is measured as the percentage of the building cost that is covered by the tax credit, and $lnG_m * lnTN_{t-1}$ is the interaction term of number of grocery stores in a MSA with the logged number of charging stations in all MSAs (the instrument in the EV demand equation). f_{mt} is a dummy variable indicating whether there exists public grants or funding for the building of charging infrastructure. T_t denotes year-quarter dummies that control for time effects common to all the MSAs. Market fixed effects φ_m control for time-invariant and MSA-specific preferences for charging stations. ς_{mt} is the unobserved shock to charging station investment, for instance, the unobserved local policies to support the charging station building.

The installed base of EVs, $\ln(Q_{mt}^{EV}+1)$ could be endogenous in that local policies could be set in response to EV demand shocks. We instrument for this variable with a set of current and past gasoline price variables.[3] The fuel cost savings from driving EVs depend on the price difference between gasoline and electricity, which varies across locations. In MSAs with higher gasoline prices, consumers may have a stronger incentive to purchase EVs. Because the installed base of EVs is the cumulative

[3] Quarterly gasoline price data for each MSA is obtained from Cost of Living Index, produced by the Council for Community and Economic Research (C2ER), which provides measure of living cost differences among urban areas. The gasoline prices for missing MSAs are estimated using the average price of the other cities in the same state.

sales of EVs, we include gasoline prices in the current quarter as well as annual gasoline prices in the past three years as instruments. For example, for the installed base of EVs in the 2nd quarter in 2013, we use the quarterly gasoline price in the 2nd quarter in 2013, the average gasoline price in 2012, the average gasoline price in 2011, and the average gasoline price in 2010 as instrumental variables. These gasoline price variables should affect the installed base but are unlikely to be directly correlated with investment decisions (i.e., other than through the installed base). Table 4.4 provides the first stage regression results using this set of instruments. The gasoline price variables are all positive and jointly significant.

CHAPTER 4: ESTIMATION RESULTS

4.1 EV Demand Regression Results

Table 4.1 Columns (a) to (d) report the ordinary least squares (OLS) estimation results for five different specifications where we add more control variables in Columns (a) to (d) successively. Column (a) only includes the four explanatory variables of interest. Column (b) adds in year-quarter fixed effects to control for time trends that are common to all EV models in all MSAs such as a national-level shift in consumer awareness of this technology. Column (c) further adds vehicle model fixed effects to control for time-invariant product attributes such as quality and brand loyalty associated with a specific vehicle model that affect consumer preference. Column (d) further includes MSA fixed effects to control for time-invariant differences across MSAs such as dealer network or a MSA's specific preference for green products (Kahn and Vaughn, 2009).

All the four OLS regression models consistently provide a positive and statistically significant coefficient on the availability of charging stations (ranging from 0.352 to 0.546) and a negative and statistically significant coefficient on the purchase price (ranging from -0.288 to -1.351). The coefficient estimates for gasoline prices are all positive, although not statistically significant in some specifications (ranging from 0.271 to 2.291). The coefficient estimates for the EV Project home charging stations are all positive, but only statistically significant when controlling for MSA fixed effects, ranging from 0.012 to 0.044. All the coefficient estimates can be interpreted as elasticities due to the log-log specification. Going from Columns (c) to (d) where MSA fixed effects are included, the EV demand function changes from being inelastic with an price elasticity of -0.753 to being elastic with a price elasticity of -1.351.

Column (e) implements an instrument variable (IV) strategy. The IV results show that a 10% increase in charging stations would result in a 10.8% increase in the EV sales, which is higher than all the OLS estimates. 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 results from these regressions imply that the increased availability of public charging stations has a statistically and economically significant impact on EV adoption decisions. This indicates that even if EV drivers can charge vehicles at home, better access to charging facilities elsewhere is still an important demand factor by, for example, alleviating range anxiety. In addition, higher gasoline prices, higher home charging subsidies and lower purchase costs would also help consumer EV adoption. Based on the parameter estimates on charging stations and purchase price variables, a back-of-the-envelope calculation shows that the demand effect from having one more charging station (the sample average is 9.9) is equivalent to a reduction of EV price by $2,120 (the average price is $33,127).

Table 4.1 EV demand equation

Variables	OLS (a)	OLS (b)	OLS (c)	OLS (d)	IV (e)
Log (No. of charging stations)	0.399***	0.411***	0.546***	0.352***	1.076***
	(0.017)	(0.017)	(0.021)	(0.037)	(0.107)
Log (gasoline price)	0.999***	1.170***	2.291***	0.301	0.161
	(0.215)	(0.316)	(0.363)	(0.194)	(0.207)
Log (retail price - tax	-0.290***	-0.288***	-0.753***	-1.351***	-1.198***
incentives)	(0.030)	(0.029)	(0.183)	(0.140)	(0.128)
	0.044	0.032	0.012	0.027**	0.044***
Log(EV Project)	(0.028)	(0.027)	(0.025)	(0.012)	(0.010)
Year-quarter fixed effects	No	Yes	Yes	Yes	Yes
Vehicle model fixed effects	No	No	Yes	Yes	Yes
MSA fixed effects	No	No	No	Yes	Yes

Note: the number of observations is 14626. The dependent variable is the logarithm of quarterly sales of an EV model in a MSA. All standard errors are clustered at the MSA level. *Significant at 10%, **significant at 5%, ***significant at 1%.

Table 4.2 First stage results for EV demand equation

Variables	Log(No. of public charging stations)
Ln(No. of stores)*ln(national stations)	0.189***
	(0.018)
log (retail price-tax incentives)	-0.185***
	(0.051)
Log(gasoline price)	0.168
	(0.117)
Ln(EV project)	-0.025***
	(0.009)
Year-quarter fixed effects	Yes
Vehicle model fixed effects	Yes
MSA fixed effects	Yes

Note: the number of observations is 14626. Standard errors are clustered at MSA level. *Significant at 10%, **significant at 5%, ***significant at 1%.

4.2 Charging Station Regression Results

Columns (a) to (c) in Table 4.3 report the OLS regression results for the charging station equation. 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 in charging station investment. For example, some MSAs may be "greener" than others and invest more on alternative fuel infrastructure. Similarly, MSAs with a higher population density and limited private installment of charging stations may have more public charging stations.

All three OLS regressions find a positive and statistically significant coefficient for the installed EV base. In Column (d), we implement an IV strategy using current and past gasoline prices. The IV results show that a 10% increase in EV fleet size would results in a 5.8% increase in charging stations. The IV coefficient estimate is higher than the OLS estimate, 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 (d) show that tax credits and the availability of public funding for charging stations have positive but statistically insignificant coefficients. Tax credits for charging stations are mainly for private installations while our dependent variable is public charging stations. The interaction term of grocery stores with lagged number of stations in all MSAs has a positive and statistically significant coefficient, consistent with our argument for using it as a relevant instrument in the EV demand equation.

Table 4.3 Charging station equation

Variables	OLS (a)	OLS (b)	OLS (c)	IV (d)
Log(No. of EV installed base)	0.374***	0.540***	0.136***	0.579***
	(0.025)	(0.028)	(0.029)	(0.172)
Charging station tax credit (%)	-0.005***	-0.003*	0.003	0.011
	(0.002)	(0.002)	(0.013)	(0.014)
Public funding or grants	0.099*	0.077	0.007	0.085
	(0.060)	(0.057)	(0.048)	(0.055)
Log(grocers)*log(national	0.042***	0.030***	0.183***	0.105***
stations)	(0.005)	(0.005)	(0.017)	(0.033)
Year-quarter fixed effects	No	Yes	Yes	Yes
MSA fixed effects	No	No	Yes	Yes

Note: the number of observations is 4236. The dependent variable is the logarithm of total number of publicly accessible charging stations in a MSA in a given quarter. All standard errors are clustered at the MSA level. *Significant at 10%, **significant at 5%, ***significant at 1%.

Table 4.4 First stage results for charging station equation

Variables	Log(No. of EV stock)
Ln(Current gasoline price)	0.396*
	(0.228)
Ln(Gasoline price last year)	3.283***
	(0.833)
Ln(Gasoline price two years ago)	2.286***
	(0.656)
Ln(Gasoline price three year ago)	3.376***
	(0.819)
Ln(No. of stores)*ln(national stations)	0.167***
	(0.018)
Charging station tax credit (%)	-0.018
	(0.016)
Public funding or grants	-0.193***
	(0.058)
Year-quarter fixed effects	Yes
MSA fixed effects	Yes

Note: the number of observations is 4236. Standard errors are clustered at MSA level. *Significant at 10%, **significant at 5%, ***significant at 1%.

CHAPTER 5: POLICY IMPACTS

5.1 Policy Simulations

The federal government has adopted several policies to support the EV industry including income tax credits for EV purchase, financial support for vehicle manufacturers and charging infrastructure, and programs for public education about electric vehicles. The Congressional Budget Office (CBO) 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 (CBO, 2012). Under the tax credits policy, EVs purchased in or after 2010 are eligible for a federal income tax credit up to $7,500. Most popular EV models on the market are eligible for the full amount. The credit will expire once 200,000 qualified EVs have been sold by each manufacturer.

Based on parameter estimates from IV regressions in Tables 4.1 and 4.3, we conduct simulations by removing the tax credit policy to examine policy effectiveness. 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 due to the feedback loops. The elimination of federal tax credits would reduce EV sales, which would reduce the installed base of EVs and in turn lead to fewer charging stations and subsequently further reduce EV sales. Our simulation results in Table 5.1 show that EV sales would have been 68,044 less (or 48.5% of the total sales) from 2011 to 2013 without the $1.05 billion worth of income tax credit to EV buyers. If we do not take into account the feedback loops, the sales contribution from the tax credit policy would only have been 39,403 (28.1% of the total sales). This implies that indirect network effects have a multiplier effect of 1.7 due to the feedback loops. The estimate excluding the feedback loop is close to CBO's estimate of 30% (CBO, 2012), which considers the price effect of the tax credit but not the role of indirect network effects in amplifying the policy effect. Further, their estimate is not based on econometric analysis of actual EV sales but previous research on the effects of similar tax credits on traditional hybrid vehicles, which run on gasoline and do not experience indirect network effects (Beresteanu and Li, 2011) (Muehlegger and Gallagher, 2011). DeShazo, Sheldon and Carson (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.

Table 5.1 Simulation Results of Eliminating Federal Tax Credits for EVs

Year-Quarters	Observed EV Sales	Counterfactual sales	Sales reduction	Percentage
2011-1	1105	763	342	30.9%
2011-2	3241	2544	697	21.5%
2011-3	2813	1802	1011	35.9%
2011-4	3900	2117	1783	45.7%
2012-1	4307	1623	2684	62.3%
2012-2	7030	2824	4206	59.8%
2012-3	9662	4788	4874	50.4%
2012-4	12665	6994	5671	44.8%
2013-1	21140	10964	10176	48.1%
2013-2	24803	13422	11381	45.9%
2013-3	25782	13509	12273	47.6%
2013-4	23747	10802	12945	54.5%
Total	140195	72151	68044	48.5%

Note: simulation results are based on EV sales data in the 353 MSAs.

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 conduct simulations under two counterfactual policies with the same budget of $1.05 billion: subsidy to charging stations investment only, and subsidy to both EV purchase and charging station investment. The results from the three policy simulations including the existing tax credit policy are presented in Table 5.2. We assume the policy period from 2011 to 2013 (i.e., no subsidy available after that). The existing tax credit policy (policy 1) has led to 68,044 more EVs from 2011 to 2013, amounting to $15,453 for one additional EV. The policy effect will continue to exist until the feedback loops die out in 2058.[4] The total sales contribution from this policy in the long-term would be 235,121, amounting to $4,472 per policy-induced EV purchase.

If instead, the government had spent the $1.05 billion evenly in each quarter during 2011-2013 on installing charging stations in all MSAs[5] (proportional to population), EV sales would have increased by 371,199 during these three years (policy 2). The cumulative sales effect of this policy until year 2058 would be 1,195,235, amounting to a unit cost of only $880, only 20% of the unit cost under the existing policy.

The last policy design (policy 3) provides $4,500 tax credit on EV purchase and uses the remaining funding ($182.5 million) to build charging stations. This policy

[4] We assume the public charging stations and the installed base of EV drivers keep increasing at a rate that was observed in the 4the quarter of 2013.

[5] The cost of an EV charging unit is between $800 and $3000, and the installation fee per site is from $3000 to $15000 per site. On average, there are 3.6 charging units per charging station (ETEC and DOE, 2013). We use the average values and assume the equipment cost of $1900 for each unit and the installation fee of $9000. Thus, the total cost of installing a charging station of an average size is: $15,840. This estimate does not include the cost of siting and should be considered as a lower bound.

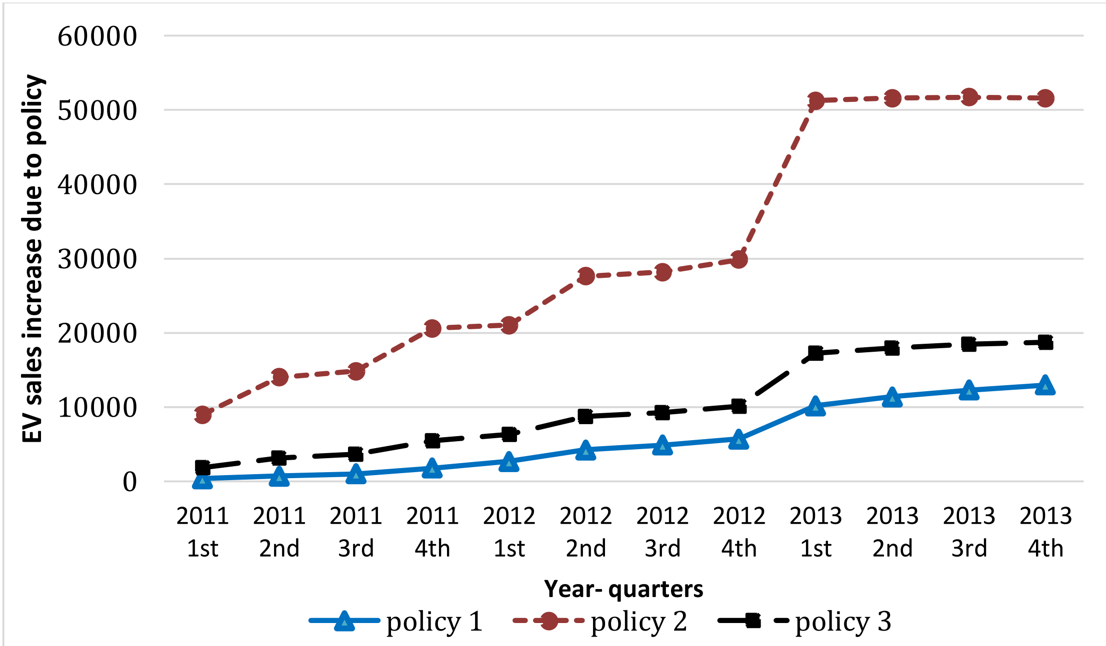
would have led to an increase of 120,742 EVs during 2011 to 2013. The cumulative sales effect till 2058 would be 477,637. As a result, the cost per policy-induced EV would be $2,201.

Table 5.2 Comparison of the existing tax credit policy with two alternative policies

Total government spending	Sales increase from $7500 tax credit (policy 1) $1.05 billion	Sales increase from alternative (policy 2) $1.05 billion	Sales increase from alternative (policy 3) $1.05 billion
2011-1	342	8954	1820
2011-2	697	13981	3100
2011-3	1011	14802	3671
2011-4	1783	20583	5418
2012-1	2684	21036	6309
2012-2	4206	27597	8739
2012-3	4874	28171	9226
2012-4	5671	29844	10059
2013-1	10176	51266	17276
2013-2	11381	51624	17968
2013-3	12273	51748	18437
2013-4	12945	51593	18719
Sales increase in 3 years	68,044	371,199	120,742
Total increase long-term	235,121	1,195,235	477,637
Total increase in 10 years	196,846	1,090,335	420,857
Government spending per EV	$4,472	$880	$2,201

Note: the vehicle increase is calculated based on comparing with the no subsidy policy scenario (eliminating $7500 tax credits). Policy 2 uses the same budget to build charging stations evenly in each quarter in all metro areas weighted by population. Policy 3 decreases the tax credit to $4,500 and uses the remaining budget to build charging stations. Total increase includes vehicle sales increase during the policy effective period (till 2058) and the increase in future years are discounted to year 2011 by a 5% discount rate.

As depicted in Figure 5.1, the second policy that only subsidizes charging station investment demonstrates a dominant advantage in stimulating EV sales. The $1.05 billion government spending on the tax credits during the three years can install about 66,380 charging stations. This is more than half of the total number of gasoline stations in the country and almost eight times of the current total number of 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. The third policy, which gives $3,000 less tax credit than policy 1 and uses the remaining budget to install charging stations, also increases the EV sales more than the existing policy. Simulation results of both policy 2 and policy 3 indicate that building charging stations is a more effective way to boost EV sales in the EV launch stage. Although our model is static in nature and does not incorporate consumer preference heterogeneity, our simulation results make intuitive sense. In reality, early adopters of EVs are likely to be less price-sensitive (reflected in our estimates of small price elasticity). They may also have a longer commute (hence buying EVs to reduce fuel costs) and therefore the availability of charging stations could be more important.



Note: Each data point represents quarterly EV sales increase due to the corresponding policy.

Figure 5.1 Comparison of Federal Tax Credits with Two Alternative Policies

Government agencies often employ the income tax credit policy to encourage the adoption of energy-efficient products such as hybrid vehicles and home appliances. The cost-effectiveness of this policy can be greatly hindered by inefficient targeting: a large portion of the funding could end up going to those who would adopt the new technology anyway (i.e., non-marginal consumers). In a market with strong indirect network effects as in the EV industry, subsidizing the complements (charging stations) could boost the adoption of the technology at a much faster pace.

The long-run simulations are based on the assumption that the driving range of EVs keeps at the current level. However, as the technology progress, the EV driving range is very likely to increase, weakening indirect network effects. In addition, the effect of the charging stations on EV demand may diminish faster than what our estimates suggest when the number of EVs is above a certain level. This would also weaken indirect network effects. As a robustness check, Table 5.2 also provides the 10-year results from the three policies and policy 2 still shows a dominant advantage.

5.2 Environmental Benefits of EV Adoption

Conventional internal combustion engines emit multiple harmful pollutants including hydrocarbons (HC), nitrogen oxides (NOx), carbon monoxide (CO), sulfur dioxide (SO2), greenhouse gases and other toxics. Parry, Walls, and Harrington (2007) estimate the external costs (health and environmental damages) from pollution and energy security to be 2.9 cents/mile. BEVs and PHEVs under electric mode do not produce on-road tailpipe emissions, but how much local pollutions and greenhouse gas emissions can be reduced by replacing conventional vehicles with EVs depend on the way that the electricity to power the vehicles is generated because the air pollutant emissions are shifted from on-road transportation to the power generating locations. In regions that depend heavily on coal or oil for electricity generation, EVs may not demonstrate an environmental advantage over gasoline vehicles. Zivin, Kotchen and Mansur (forthcoming) estimate marginal emissions of electricity demand 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 am even generates more emissions than the average conventional gasoline vehicle on the road.

To assess the environmental benefits of the EV subsidy policies, we match each MSA with the corresponding eGrid subregion's[6] electricity fuel mix to estimate the external cost savings from replacing one EV with one convention vehicle. To assess the external cost savings from replacing gasoline cars with EVs, we need to compare the external costs per mile for gasoline vehicles with the external costs per mile for EVs. Since both conventional vehicles and EVs contribute to congestion and on-road accidents, we only compare external costs from local pollution, greenhouse gas emissions and oil dependency. Table 5.3 lists parameter values that are drawn from the literature to supplement our estimate of the external cost savings from EVs. The external cost per mile driven for BEVs is calculated as the external cost of electricity generation (per kWh) multiplied by the fuel economy of BEVs (kWh per mile). The external cost per mile driven for PHEVs is calculated as the weighted sum of the external cost per mile under the electric model and the gasoline mode. We assume the share of electric mode among vehicle miles traveled to be 70% (AFDC, 2014).

[6] eGrid subregions are defined by US Environmental Protection Agency using the transmission, distribution and utility service territories of power plants and do not follow geographic state boundaries. There are 26 subregions and each covers a unique areas of the country.

Table 5.3 Parameters in environmental benefits analysis

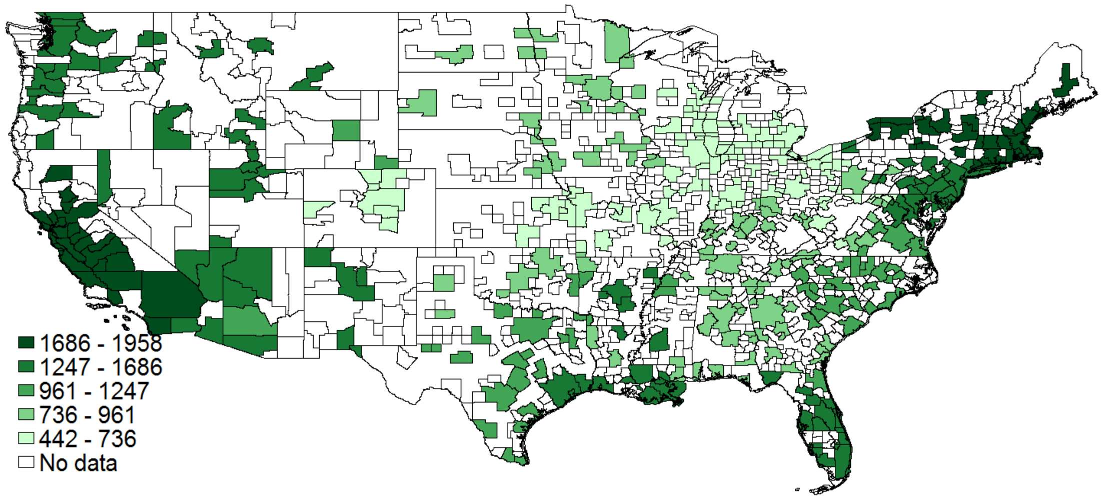
Parameters	Value	Source
PHEV electricity usage	0.36 kWh/mile	AFDC (2014)
BEV electricity usage	0.34 kWh/mile	AFDC (2014)
% of PHEV miles driven on electricity	70%	AFDC (2014)
External cost per mile for gasoline cars	2.9 cents/mile	Parry et al. (2007)
External cost of electricity from coal	8.54 cents/kWh	Sundqvist & Soederholm(2002)
External cost of electricity from oil	12.19 cents/kWh	Sundqvist & Soederholm(2002)
External cost of electricity from natural gas	3.51 cents/kWh	Sundqvist & Soederholm(2002)
External cost of electricity from nuclear	1.08 cents/kWh	Sundqvist & Soederholm(2002)
External cost of electricity from hydro	0.43 cents/kWh	Sundqvist & Soederholm(2002)
External cost of electricity from wind	0.43 cents/kWh	Sundqvist & Soederholm(2002)
External cost of electricity from solar	1.02 cents/kWh	Sundqvist & Soederholm(2002)
External cost of electricity from biomass	3.59 cents/kWh	Sundqvist & Soederholm(2002)

The external cost per kWh of electricity is calculated as the sum of the external costs of all the energy sources used in the process of power generation weighted by their share in the fuel mix. eGRID sub-region data on the electricity fuel mix is obtained from eGRID database (2010)[7]. Because different regions use different fuel mixes for electricity generation, the external cost of one kWh of electricity varies across regions. In places where the primary electricity-generating source is coal or oil, the external cost per kWh of electricity is relatively high and EVs may not demonstrate a big advantage in terms of reducing externalities. Assuming a vehicle life-time of 10 years and the annual vehicle miles traveled of 15,000 miles, the total life-cycle external cost savings from a BEV and PHEV is obtained by multiplying the external cost saving per mile with the total discounted life-cycle vehicle miles (at an annual discount rate of 5%).

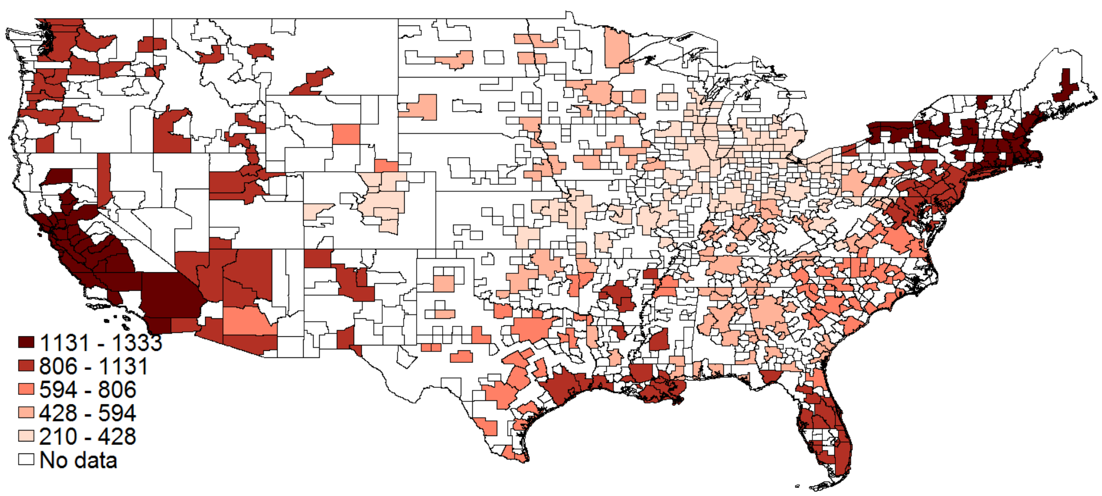
[7] The Emissions & Generation Resource Integrated Database (eGRID) is a comprehensive source of data on the environmental characteristics of almost all electric power generated in the United States. It is maintained by U.S. Environmental Protection Agency.

Figure 5.2 depicts the spatial differences in cost saving estimation across MSAs. The life-cycle average cost saving from replacing a gasoline vehicle with a BEV is \$1,181 from our assessment, with a range from \$442 to \$1,958. The life-cycle average cost saving of a PHEV is \$758 with a range from \$210 to \$1,333, assuming 70% of the annual PHEV miles are driven on electricity. Based on these estimates, the total life-cycle external cost savings from the federal tax credit policy implemented between 2011 and 2013 (policy 1) to be \$0.23 billion in 2011 term. Policy 2 would generate the total savings in external costs of \$1.11 billion and policy 3 \$0.44 billion. If only considering the environmental benefits in the future 10 years, the total external cost savings are \$0.20 billion, \$1.03 billion and \$0.40 billion respectively.

Panel (a) Cost saving from a BEV



Panel (b) Cost saving from a PHEV



Note: The external cost savings are calculated by comparing the life-cycle external cost of BEVs or PHEVs with gasoline vehicles and are measured in dollars.

Figure 5.2 External Cost Saving from Adopting EVs

Caveats are in order regarding these estimates. First, the calculations are based on the assumption that newly purchased EVs replace conventional gasoline vehicles. Therefore, the benefits would be overestimated if EVs instead replaced traditional hybrid vehicles. The exact substitution pattern in the automobile market especially with alternative fuel vehicles is not well understood. Second, the tax credits for electric vehicles can generate leakage: the policy relaxes the stringency of the Corporate Average Fuel Economy (CAFE) Standard and therefore could induce more sales of less fuel-efficient vehicles. This would limit the policy effect on reducing overall gasoline consumption and emissions. Analysis on this issue would require a different modeling framework that would incorporate firm decisions. Third, our calculations assume that EVs and gasoline vehicles contribute to on-road congestion and accidents at the same level. In reality, EVs may cause more congestion or accidents than gasoline vehicles since drivers could drive more due to the lower fuel cost of driving (the rebound effect). In some states where solo drivers of EVs are allowed to use high occupancy vehicle lanes on major freeways, car poolers will face higher congestion costs and the welfare loss due to the policy could dominate any intended environmental benefits (Bento et al, 2014).

The overall cost-effectiveness of the policy requires more than just comparing the environmental benefits of the tax credit policy and government spending. There are additional policy goals including helping EV producers climb up the learning curve and reducing production costs. A rigorous analysis of the cost-effectiveness would necessitate consumer welfare calculation and the impact on firm profits in a market equilibrium model.

CHAPTER 6: DISCUSSION AND CONCLUSION

An active governmental role to promote the EV technology can be justified by: (1) the external costs from gasoline consumption in the U.S. are not properly reflected by the gasoline tax (Parry and Small, 2005), and (2) information spillovers among consumers and firms are often present in the early stage of new technology diffusion (Stoneman and Diedern, 1994). Indirect network effects in the EV market, if they exist, would compound these market failures through feedback loops and would further strengthen the argument for government intervention.

This study empirically quantifies indirect network effects in this market and evaluates the impact of the federal income tax credit for EV purchases. Our analysis estimates the elasticity of EV adoption with respect to charging station availability to be 1.08 and the elasticity of new charging station investment with respect to the installed base of EVs to be 0.58. These indirect network effects enhance the effectiveness of the tax credit policy, which has contributed to 48.5% of the EV sales during 2011 to 2013 and will continue to exhibit a positive effect on the market for many years through feedback loops even if the policy had stopped in 2013.

Our findings offer some insights for policy design to promote the 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 low price-sensitivity of early adopters and strong indirect network effects from charging stations on EV demand. Second, the environmental benefit of replacing conventional gasoline vehicles with EVs critically hinges on the fuel mix of electricity generation, which varies greatly across regions. The spatial variation limits one-size-fit-all policies. Priority should be given to regions with cleaner electricity generating fuel mixes through regionally targeted subsidies.

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