

Master's Thesis in Economics

Network effects and compatibility in the Swedish electric vehicle market

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Abstract

The Swedish market for electric vehicles displays network effects due to the interdependence between electric vehicle sales and charging station deployment. This study looks at network effects under incompatible charging standards and demonstrates the potential effects of increasing the level of compatibility. Using panel-data on the vehicle sales and charging station availability in 21 counties from 2011 to 2017, I find that there exists positive and significant network effects on both markets of approximately equal magnitudes, implying a mix of policy instruments is necessary to increase electric vehicle adoption rates. Using a stylized model, I find that steady-state equilibrium car sales and charging station stock could increase by approximately 1.25 % and 6.66 % respectively.

Supervisor: Li Chen

Key words: electric vehicles, network effects, compatibility

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Table of contents

1.	Introduction	3			
2.	Background	8			
Т	he Swedish electric vehicle market and types of charging	8			
C	harging standards and compatibility	9			
S	ubsidies, tax credits and other demand side policy actions	10			
3.	Data and descriptive statistics	12			
4.	Model	13			
Ν	Nodel setup	13			
5.	Empirical Framework	16			
E	lectric vehicle demand equation	16			
C	harging station deployment equation	17			
6.	Estimation results & Analysis	19			
R	legression results for EV demand	19			
R	Regression results for charging station deployment21				
R	Robustness check				
P	olicy simulation	23			
7.	Conclusion	23			
8.	Suggestions for future research	25			
Ref	References				
Арр	Appendix				

1. Introduction

In emerging markets, the way firms choose to compete determines the nature of how consumers interact with the market. This is especially the case for markets that exhibits network effects. Network effects stem from actions and outcomes on one market affecting outcomes on another independent market. The decisions of the firms regarding compatibility determines the network size, the nature of competition and how consumers derive utility from the value added through network effects. Common standards increase consumer take-up and may benefit consumers through increased variety. Incompatible standards give rise to a situation where the firms compete for the market and may increase the scope for monopoly pricing. This leads to a trade-off between consumer take-off and pricing power. This has additional consequences for consumer welfare and has thus generated an intense debate among policy makers and antitrust authorities on a wide range of issues, such as manufacturing and digital markets¹.

This thesis assesses the network effects on the Swedish market for electric vehicles, which has grown substantially in recent years. The share of new car sales made up of electric vehicles in Sweden is the third highest in Europe and reached 6.3 % in 2017 (IEA, 2018). Electric vehicles (EV) have attracted large public support as it is increasingly being seen as a vital tool for climate change abatement, an engine for innovation spill-over and a way to lower dependence on fossil fuels. As a response to this, along with increasingly stringent environmental regulations, car manufacturers are increasing their investments into greener technology and have introduced battery electric vehicles (BEV) and plug-in hybrids vehicles (PHEV) into their product portfolios².

As with traditionally fueled vehicles, along with other alternative fuel sources, electric vehicles require benefit from a refueling infrastructure for increased mobility of drivers and widespread consumer acceptance. As a result of this, investments into charging stations has

¹ For example, Microsoft were forced to make Word available on Macintosh computers in order to limit their market power (United States v. Microsoft Corporation (2001)).

² The European Commission has introduced legislation through the 2030 EU Climate and Energy Frameworks that target a 40 % reduction in the level or greenhouse gases (from the 1990 level) requiring a 30 % decrease in sectors not covered by the EU ETS (European Commission, 2014).

increased in line with the growth of the EV market. The relationship in the growth curves of both markets can be seen in Figure 1 (EV sales are included in units of ten).

To the dismay of consumers, car manufacturers have aligned themselves behind competing standards. For level 2 charging there is some scope for compatibility through adapters (E-mobility, 2018a) but for level 3 charging the standards are incompatible (The charging standards will be discussed in detail in section 2).

This thesis uses a new dataset of all EV sales and publicly available charging stations in 21 counties from 2011 to 2017 to estimate the network effects of both markets using two structural equations: an EV demand equation to estimate the effect of charging station deployment on EV demand, and a charging station deployment equation to estimate the effect of the size of the EV fleet on charging station deployment. Observing endogeneity from simultaneity in both equations and endogeneity of price in the EV demand equation, I use an instrumental variables (IV) approach to estimate the parameters. For the EV demand equation I use car model subsidy and a Berry, Levinsohn & Pakes instrument to control for endogeneity of price. For the simultaneity bias I use the number of grocery stores, interacted with the lagged number of charging stations in all other markets (interacting national demand shocks with local market conditions), as an instrument. For the charging stations deployment equation I include an instrument of current and lagged gasoline prices interacted with the average winter temperature. Using different model specifications, I find statistically and economically significant network effects on both markets. The parameter estimates show that a 10% increase in the number of charging stations increases vehicle sales by approximately 4.1 %, whereas a 10 % increase in the size of the EV fleet increases the number of charging stations by approximately 3.9 %. Moreover, I find that the price sensitivity of electric car owners is lower than in traditional car markets likely due to a high percentage of early adopters.

In a second step, using the parameter estimates I present the steady-state equilibrium values derived from the structural equations under different levels of compatibility and find potential welfare improvements from increases in the level of compatibility. Using the average car model compatibility of 0.63 as a proxy for the overall compatibility level, I find that both car sales

and the number of charging stations could increase by approximately 1.25 % and 6.66 % respectively when moving from the observed level of compatibility to full compatibility.

This thesis contributes to three strands of literature. Firstly, this study contributes to the literature on the effects of compatibility on welfare. From a theoretical standpoint these effects are unclear as the private incentives (increase in industry profits from larger consumer takeup) may be higher, or lower, than the social incentives (increase of consumer surplus from lower market power) (Katz & Shapiro, 1985). Thus, the effect of compatibility is an empirical question. Previous studies in the topic have found significant gains to consumer welfare as result of compatibility (Ho, 2006) on insurer-hospital networks; Li (2017) on electric vehicle charging standards)³. However, as firm incentives change due to compatibility policies, this may offset some of the consumer welfare gains. Lee (2013) finds that exclusivity in the videogame industry benefit new entrants rather than incumbents, which contrasts with the common view of exclusivity as a means of deterring entry. Similarly, Knittel & Stango (2011) find that strategic incompatibility in ATM fees is mainly observed by larger banks with smaller banks utilizing higher deposit fees while Ishii (2007) find that elimination of ATM surcharges would substantially decrease market concentration, raise consumer surplus and lower overall industry profits. This thesis is most related in topic to Li (2017) who uses a structural model of vehicle buyer behavior (using the discrete-choice framework of Berry (1994)) and charging stations (built by car manufacturers) to simulate the effect of compatibility policy on electric vehicle adoption and charging stations building patterns. It finds that allowing consumers to access all charging stations increases the market share of electric vehicles and reduces firms' incentives to invest in charging stations by 54 % of the original investment level. However, Li (2017) uses a method that is not applicable to the Swedish market as most charging stations in Sweden are not built by car manufacturers themselves, but by third parties. Moreover, this thesis is most related in method to Li et al. (2017) that looks at network effects in the US market for electric vehicles. They find that a 10 % increase in the charging station deployment would increase electric vehicle sales by 8 %, and a 10 % increase in the size of the electric vehicle fleet would increase the number of charging stations by 6.1 %. However, this method does not account for the incompatibility in the EV market which creates a potential source of bias for

³ Although policy makers should not only focus on consumer welfare but on product attributes as incompatibility reduces the consumers' ability to mix and match (Knittel & Stango, 2008).

the estimates. I enrich this model with the introduction of level of compatibility (see section 4).

Secondly, this study contributes to the literature on electric vehicle demand and the subsidy impact of subsidies for electric vehicles. The main findings in this field is that consumers do respond to subsidies, to different extents, and that those who take advantage of the subsidies are generally wealthier than average and the subsidy design is important to reach beyond the inframarginal consumers and thus a wider market (Holtsmark & Skonhoft (2014), Borenstein & David (2015), Huse & Lucinda (2014), Chandra et al. (2010)). Moreover, gasoline price has been found to affect the market share of electric vehicles partly through growth in plug-in hybrid sales crowding out less fuel-efficient vehicles (Gallagher & Muehlegger (2011), Chandra et al. (2010), Diamond (2008), Hidrue et al. (2011), Berestanu & Li (2011).

Finally, this study contributes to the literature on network effects and feedback loops between electric vehicle adoption and charging station construction. Studies find that the cost-effectiveness of charging station subsidies on electric vehicle sales is higher than price subsidies through positive responses from one side of the market to the other (Li et al. (2017) looks at the U.S. market and Springel (2016) considers the Norwegian market). However, it is unclear if the same relationship would hold in the Swedish market. Nordlund et al. (2017) find that 80 % of electric vehicle drivers in Sweden live in independent houses, compared to 50 % for the general population, which increases the ability for domestic charging and they find heterogeneity in charging behavior for plug-in hybrid and battery-electric vehicles. Moreover, survey data from 300 electric car users by the City of Stockholm (2016) find two distinct groups of charging behavior: charging while parking for several hours and almost exclusively fast charging. These results suggest that the different types of charging serve different consumer needs and that the location of the charging station must be determined in accordance with the type of need the station would serve.

The thesis is structured in the following manner. Section 2 describes the market for electric vehicles in Sweden, relevant technical details about charging standards and stations as well as state and local government subsidies and incentives. Section 3 provides descriptive statistics and information on the data set. Section 4 presents a model of indirect network effects under

incompatibility. Section 5 presents the empirical framework and identification strategy. Section 6 presents the regression results and discussion. Section 7 concludes. Section 8 suggest ideas for future research in the topic.

2. Background

This section gives a brief description of the Swedish market for electric vehicles, the different types of charging, the different standards for charging as well as policy instruments used for electric vehicle adoption.

The Swedish electric vehicle market and types of charging

As awareness of environmental issues become more prevalent in public discussion, electric vehicles have increasingly become viewed as an answer to limiting greenhouse gas emissions from stemming from the transport sector⁴. Since the beginning of the wide-spread market introduction on the Swedish market, when there were only a handful of models to choose from, increased investment in green energy from traditional car manufacturers to comply with increasingly stringent environmental regulations and changes in consumer demand for environmentally friendly vehicles have led to many traditional car manufacturers including electric and plug-in hybrid vehicles in their product portfolios ⁵. Figure 2 shows the annual EV sales in Sweden from 2011 to 2017, which exhibits an exponential relationship with an average annual growth rate of roughly 130 % and both industry and government predict the market to grow to six times its size by 2023 (Power Circle, 2018).

Electric vehicles can be broadly classified into two types: battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV). They differ in that BEVs are solely powered by an internal battery whereas PHEVs can use gasoline or diesel as an additional back-up fuel source, also known as ICE. As of 2017 PHEVs made up 74 % of electric vehicles in Sweden (see Figure 3a) largely due to an increase in the product range through increased production by traditional car manufacturers. Moreover, the market share of new car sales for EV is among the highest in Europe and the market share of the existing fleet of vehicles passed 2 % by the end of the last quarter 2017 (see Figure 3b). As with traditional fuel sources, a refueling infrastructure is required for the mobility of the drivers. As electric vehicles can be charged through a regular outlet, a refueling infrastructure does not seem as crucial as for traditional cars but the speed, or lack thereof, of charging through regular outlets make them unsuitable

⁴ In 2016 the greenhouse gas emissions from domestic transports amounted to approximately 30 % of total emissions (SCB, 2016).

⁵ The EU has set goals to reduce emissions from vehicles industry-wide by 30 % by 2030 (Euractiv, 2018).

for long-distance trips. The frequency and coverage of commercial charging stations has increased year-by-year and shows a clear relationship with the increase in the size of the electric vehicle market in Sweden (see Figure 1).

There are three choices for speed of charging. Level 1 represents charging through a regular wall outlet. The low power output of level 1 charging essentially limits it to an over-night option for charging. Level 2 charging stations have a higher power output, and hence faster charging speed, than level 1 charging. These take four to six hours, depending on the size of the battery, to fully charge a vehicle and are typically installed at shopping malls and commuter parking, as well as in houses. For everyday commuting and most travel this provides a sufficient charging option for most drivers. However, for long-range inter-city travel, a faster option might still be necessary. Level 3 chargers, of fast chargers, use direct-current (DC) to deliver high-power electricity to a vehicle. These work together with a transformer and can recharge a vehicle to 80 % in approximately 30 minutes.

Charging standards and compatibility

As mentioned, electric vehicles have three main types of charging. Level 1 represents regular outlets and are available and uniform for all BEVs and PHEVs. Recognizing the importance of mobility and the possible effects of range anxiety of the drivers, most new electric vehicles come with level 3 charging compatibility. Unlike the United States, level 2 charging, subject to a standard since 2013 (European Commission, 2013) is rapidly industry-wide moving to Type 2 outlets which is today used in approximately 70 % of electric vehicles (compared to 29 % for Type 1 outlets)⁶. As the market moves towards a common standard for level 2 charging, level 3 charging remains divided. There are three main different, and incompatible standards for level 3 charging: Chademo, CSS (or SAE Combo/ComboEU) and Tesla Supercharger. The Chademo (coming from "CHArge de Move") standard was developed by Japanese car manufacturers and was released in 2010 in conjunction with the release of the Nissan Leaf, a small affordable BEV. The Combo (SAE J1772) standard was developed through the Society of Automotive Engineers (SAE) and was announced in 2012 before first being released in 2014

⁶ A charging standard is made of up two parts: a set of electronic communications between the vehicle and the charging station and a physical connector (Li, 2017).

through the entry of BMW i3. This is the standard for level 3 charging that the EU decided on in 2013 and is the fastest growing standard and most common in new car models⁷. Finally, the Tesla standard was developed internally by Tesla Motors (now Tesla) which was released in with the introduction of the Tesla Model S. In contrast to the United States, Swedish commercial charging stations are generally built by public and private actors but rarely by carmanufacturers. In conjunction with the stricter emission level goals set in November 2017 stating greenhouse gas emissions should be cut by 30 % industry-wide until 2030, the Commission stated it would invest €800 million into electric vehicle charging infrastructure throughout the European Union (Financial Times, 2017).

Subsidies, tax credits and other demand side policy actions

Support for electric vehicle adoption has grown and is still growing, both from the public sector as well as individuals. Government subsidies for electric vehicles in Sweden are carried out in different ways. *Miljöbilspremien* was introduced in 2007 and gave a tax credit of 10 000 SEK to new cars that met the stated criteria of emission levels. The effects of this reform were muted and Huse & Lucinda (2014) found that although the program increased the market share of green cars (emission levels of 50 g CO2/100 km or less), most consumers would have bought a green car regardless of the subsidy. In 2011 the method of environmental classification of cars was changed from environmental classes to emission classes. The vehicles meeting the new criteria would be exempt from road tax for the first five years after the purchase. In addition, *Supermiljöbilspremien* was introduced which gives a rebate of up to 40 000 SEK for individuals⁸ on the difference in price between vehicles that meet the conditions and those who do not. This was introduced in an effort to reduce the demand frictions of electric vehicle adoption caused by the higher prices for electric vehicles through higher manufacturing costs due to scale disadvantages and the lack of a refueling infrastructure⁹. In 2016 the subsidy was changed to 40 000 for electric vehicles and 20 000 for plug-in hybrids. The subsidies available

⁷ The Commission decided that ComboEU would be the standard for level 3 charging but that it would allow newly built stations to be equipped with the Chademo standard during a transition period until 2019. Recharging stations that are built within three years of the entry of the directive may remain in service (European Parliament, 2013).

⁸ For businesses the subsidy is 35% of the price difference up to 40 000 SEK. Moreover, a 40 %, to a maximum of 10000 SEK, reduction in taxation is applied to company cars for BEV and PHEV (ACEA, 2018)
⁹ The European Commission estimates that the emissions goal for 2030 will lead to an increase of €1000 in manufacturing costs by 2030 (BBC, 2017).

through *Supermiljöbilspremien* are allocated through the federal budget and represent a fixed annual sum from which one can apply for money. The budgeted amount for 2017 was 700 million SEK of which approximately 420 million was used (Transportstyrelsen, 2018).

There are available subsidies for both individuals and businesses in the installation and construction of charging stations respectively. For individuals, this subsidy is through a rebate of up to 50 % or 10 000 SEK for the cost of purchase and installation of residential charging stations. Since 2015 individuals and businesses may apply for tax credits for installation of charging stations through ROT financed by *Klimatklivet*. For businesses this rebate covers up to 50 %, or 20 000 per charging point, of the cost of installation. The budget for 2015-2020 has been set at 3.2 billion SEK of which 113 million SEK has been awarded as of the end of 2017 (Naturvårdsverket, 2017). The costs of building charging stations range from 60.000-80.000 for level 2 stations and 350.000-800.000 for level 3 charging stations (Emobility, 2018b).

3. Data and descriptive statistics

Table 1 shows summary statistics of the variables included in the regressions. The upper box shows the mean and standard deviation for the variables included in the EV demand equation and the bottom box shows the mean and standard deviation for the charging station deployment equation. The sales of EV model is measured as the sum of annual sales of a vehicle model in a county. Moreover, the no. of compatible charging stations shows the number of stations in the dataset that have a listed standard that is compatible with at least one of the car model's standards. This entails that the number of compatible stations can be expressed as a function of the total number of stations and a variable for the fraction of compatibility (this is explained formally in section 4). Price is included as the manufacturer suggested retail price (MSRP) net tax incentives is endogenous in the model (this is discussed in detail in section 5). Mean income and population density are measured at a yearly basis. Mean income is used as a proxy for income and reflects the purchasing power of the county. Population density is included to control for both the heterogeneity in car necessity as well as the availability of public transport. The average commute time is measured as a weighted average of the estimated commute time for all vehicles sold within the county in the year. As I only have data on municipality level, I use the type of municipality as reference and weigh the average daily distance commuted by gender and assume the cars owned by businesses to be at the sample mean for the type of municipality. This is added up to give an estimate for the average commute for the entire county. Gasoline prices, the number of grocery stores, lagged number of grocery stores and the average winter temperature are included as instruments.

To estimate the indirect network effects in the Swedish market for electric vehicles I construct a data-set with five main elements, giving me a panel of 21 markets from 2011 to 2017. First, I use market-level data on the existing fleet of electric and plug-in hybrid vehicles in Sweden purchased from *Power Circle*. This set contains information on the date of purchase, date of registration, home municipality of the owner, gender as well as aggregated market information. Using the date of registration as my date of sale, I sum the sales of each car model within a county in a year (this is the dependent variable in the EV equation). To avoid including secondary markets I only include vehicles with a date of sale that is within two years of the date of construction. I delimit the market as the home county of the individual due to few observations at the municipality level and the same reasoning is applied to using year instead of quarter as the time dimension. In addition, the control variables used in the regressions are to the best of my knowledge only available as annual observations. Second, I merge the car sales with data on model-level information collected from *Facit, the Swedish Consumer Protection Agency (Bilsvar)* and *Power Circle* such as suggested retail price and battery capacity. The price that is included in the regression is the net of taxes price including the available price subsidies at the time of purchase. I assume that each buyer takes advantage of all available price subsidies. Third, I include data on commercial charging stations generously provided by *Uppladdning.nu*. This set includes information on the date of construction, location and available outlets and standards of 2761 charging stations in Sweden. Figure 4 shows the geographic spread of charging stations in Sweden.

Fourth, I use data on average income and population density provided by *SCB (Statistics Sweden)*. Fifth, I use survey data from *Trafikanalys* on differences in car commuting habits between counties.

4. Model

This section presents a simple stylized model of indirect network effects and incompatibility that illustrates how equilibrium conditions are impacted by different levels of (in)compatibility.

Model setup

My model builds on Li et al. (2017). The model assumes that the sales of electric vehicles $q_t(N_t, p_t, x_t)^{10}$ is a function of the number of available charging stations (N_t) , the price of the vehicle (p_t) , as well as other product characteristics that affect consumer choices (x_t) . The fleet size, or installed base of EVs, is a cumulative sum of the sales minus scrappage at time t, presented as $Q_t = \sum_{h=1}^t q_h * s_{t,h}$, where $s_{t,h}$ is the survival rate at time t for vehicles sold in time h. The number of constructed charging stations at time t $(N_t(Q_t, z_t))$ is a function of the market size of EV (Q_t) and variables that affect the fixed cost of investment (z_t) . These functions can be illustrated as follows.

$$\ln(q_t) = \beta_1 \ln(N_t) + \beta_2 \ln(p_t) + \beta_3 \ln(x_t)$$
(1)

¹⁰ For simplicity I have dropped the market subscript m from the equation.

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

The EV equation is derived from the discrete-choice model of vehicle demand and logit model by Berry (1994). This model implicitly assumes that consumers are myopic and only consider electric vehicles and do not consider future evolution of prices or product characteristics¹¹. The equation of charging stations is derived from an entry model of Gandal et al. (2000).

The parameters β_1 and γ_1 capture the indirect network effects on both markets, and if $\beta_1 \neq 0$ and $\gamma_1 \neq 0$ there exist feedback loops magnifying shocks to the system. If these are both positive (or negative), they will amplify shocks to the system whereas different signs will dampen shocks to the system.

To incorporate the effects of incompatibility into the model I model the equations as follows.

$$\ln(q_t) = \beta_1 \ln(\psi N_t) + \beta_2 \ln(p_t) + \beta_3 \ln(x_t)$$
(3)

$$\ln(N_t) = \gamma_1 \ln(\psi Q_t) + \gamma_2 \ln(z_t) \tag{4}$$

Where $0 < \psi \le 1$ shows the level of compatibility where 1 implies perfect compatibility¹². As above, the growth function of the installed base of EVs is $Q_t = \sum_{h=1}^t q_h * s_{t,h}$. Assuming $\ln(p_t) = p, \ln(z_t) = z, \ln(x_t) = x, s_{t,h} = \delta$ we can input equation $\ln(N_t)$ into equation $\ln(q_t)$.

$$\ln(q_t) = \beta_1 \gamma_1 \ln(q_t + \delta Q_{t-1}) + \beta_1 \gamma_1 \ln(\psi) + \beta_1 \gamma_1 z + \beta_2 p + \beta_3 x$$
(5)

¹¹ The model of Barry (1994) includes an outside good and the dependent variable is included as the market share of the car model. I choose the dependent variable to be the number of sales as the EV market is still a relatively small share of the overall car market and it can be argued that the EV market consumers do not consider traditionally fuelled vehicles as substitutes to electric vehicles.

 $^{^{12}}$ The value of ψ varies over time, market and car model but is treated as fixed in this model for ease of calculation. An alternative model setup could treat the level of compatibility as endogenous.

Further, I denote $c = \beta_1 \gamma_1 z + \beta_2 p + \beta_3 x$ as this is constant with respect to q_t . For t = 1, $Q_{t-1} = 0$, which gives us.

$$\ln(q_1) = \beta_1 \gamma_1 \ln(q_1) + \beta_1^2 \gamma_1 \ln(\psi) + c$$
(6)

Rearranging yields $q_1 = \exp(\frac{c + \beta_1^2 \gamma_1 \ln(\psi)}{1 - \beta_1 \gamma_1})$.

Using the steady-state condition $q_t = q_{t-1} = q^*$, we get the equilibrium values¹³.

$$q^* = \exp(\frac{c + \beta_1^2 \gamma_1 \ln(\psi) - \beta_1 \gamma_1 \ln(1 - \delta)}{1 - \beta_1 \gamma_1})$$
(7)

$$N^* = \exp(\gamma_1 [\frac{c + \beta_1^2 \gamma_1 \ln(\psi) - \beta_1 \gamma_1 \ln(1 - \delta)}{1 - \beta_1 \gamma_1}] - \gamma_1 [(1 - \delta) - \ln(\psi)] + \gamma_2 z)$$
(8)

This model suggests that temporary shocks to the system does not have an impact on the equilibrium values but can accelerate growth to the equilibrium levels. The level of compatibility $\ln(\psi) < 0$ has a positive relationship with the equilibrium values and these increase as the market moves toward perfect compatibility. When $\psi = 1$, the equilibrium values are the same as in Li et al. (2017). Furthermore, the price elasticity of demand matters for the effectiveness of the EV side of the market. A higher price elasticity of demand implies that smaller price subsidies are required to stimulate EV adoption than for lower elasticities. This model provides the theoretical framework for the empirical analysis.

¹³ Another possible steady-state is $q^* = N^* = 0$.

5. Empirical Framework

To estimate the magnitude of the indirect network effects on the EV market and the market for charging stations, I run regressions on equations $\ln(q_t)$ and $\ln(N_t)$.

Electric vehicle demand equation

I estimate the EV demand model I use the following equation:

$$\ln(q_{kmt}) = \beta_0 + \beta_1 \ln(N_{mt}) + \beta'_2 X_{kmt} + \varepsilon_{kmt}$$
(9)

where the subscripts k, m and t index car model, market (county) and year respectively. q_{kmt} is the sales of car model k in market m in year t^{14} . N_{mt} denotes the number of compatible charging stations constructed in the county by the end of the given year¹⁵¹⁶. I choose to use the number of stations rather than the number of outlets to better represent the infrastructure of the charging network which I believe gives a better insight into the network effects. X_{kmt} is a vector of covariates such as estimated purchase price, mean income and other control variables. I do not include neither county- nor year fixed effect due to the sample size as well as being my main sources of variation. This limits my analysis as I do not control for national demand shocks that are common across counties or geographic time-invariant heterogeneity such as local preferences for green vehicles. ε_{kmt} represents time- and market variant unobserved demand shocks such as local government subsidies and sales promotions. Moreover, I include car model fixed effects to control for unobservable consumer preferences such as brand premiums.

Failing to control for price endogeneity can lead to negative bias in the estimate for the price coefficient (Berry, Levinsohn & Pakes 1995; Beresteanu & Li 2011). To deal with this endogeneity I use an IV strategy consisting of two parts. First, I include the subsidy per car which varies over time and car model. Controlling for product characteristics such as horsepower and battery range, the price subsidy is plausibly uncorrelated with ε_{kmt} . Second,

¹⁴ I assume all vehicle models are available all years from the first observed purchase.

¹⁵ To deal with zero values I add one to q_{kmt} , N_{mt} . In the analysis I show what happens when removing the zero values.

¹⁶ The level of compatibility could also be included as an independent term but I choose to include it as an interaction due to multicollinearity issues. An earlier analysis found showed a 0.1 unit increase in compatibility is associated with a 0.7 % increase in EV sales.

I use a BLP instrument which is the average characteristic of other products in the market, I use the battery effect as the characteristic in question¹⁷. This affects the markup a firm is able to charge and is uncorrelated with ε_{kmt} if the product characteristics are generated though an exogenous process of development.

The charging station variable is also endogenous due to simultaneity. I use an interaction between the number of grocery stores within the county and the lagged number of charging stations in all other markets. Grocery stores, in particular supermarkets, are places with large potential for charging stations and may construct charging stations both for competitive (attracting customers) and environmental (increasing green credentials) reasons. Moreover, the number of charging stations in the county is positively correlated with the number of grocery stores ($\rho = 0.76$). This variable deals with county level variation but does not address temporal variation. Introducing a lagged term for the number of charging stations in other markets which represents trends in investment, investor confidence as well as, to some extent, the expectations of EV sales. The intuition of this is that national shocks to charging station investment disproportionally effect different markets and that markets with more grocery stores will be affected more than others.

Charging station deployment equation

Using the model of Li et al. (2017) derived from an entry model where profits depend on the installed base of electric vehicles and the number of stations in the market, the total number of charging stations can be estimated through the following equation:

$$\ln(N_{mt}) = \gamma_0 + \gamma_1 \ln(Q_{mt}^{EV}) + \gamma_2' Z_{mt} + \varsigma_{mt}, \qquad (10)$$

where N_{mt} denotes the number of public charging stations constructed by year t in market m and Q_{mt}^{EV} denotes the installed base of compatible EVs by year t in market m. Z_{mt} is a vector of covariates such as estimated cost of construction and the number of grocery stores interacted with the lagged number of charging stations in all other markets (the instrument in the EV equation above). As above, I do not control for time or market fixed effects. ς_{mt} represents

¹⁷ BLP instruments are named after Berry, Levinsohn & Pakes (1995).

unobserved shocks to charging station investment such as local government policies support charging station investment.

As above, endogeneity due to simultaneity arises in this equation as well. Both N_{mt} and Q_{mt}^{EV} are stock variables with the inflows being determined at the same time. This implies that timevarying and MSA-specific shocks to investment decisions could be correlated with current EV sales, which are part of the installed base of EVs. To control for this endogeneity, I include the current and lagged gasoline prices. The fuel costs savings from driving EVs depend, in part, on the price differential between gasoline (or diesel) and electricity¹⁸. Thus, higher gasoline prices may increase consumers' incentives for EV adoption. The gasoline price in my data varies over time but does not vary over markets. To deal with this I use the same reasoning as in the EV equation. I interact the gasoline price with the average temperature in January in the county, giving me spatial variation in the variable. Temperature has an effect on the battery capacity of a vehicle as colder weather increases the connective ability of the battery and thus reduces the range. This should arguably affect the number of EVs within the market but should not affect investment decisions directly (other than through the number of vehicles).

¹⁸ In an earlier analysis I used the difference between the gasoline price (SEK/L) and the electricity price (SEK/8.82kWh) and got qualitatively similar results. The value 8.82 comes from the equivalent between one gallon of gasoline and 33.4 kWh of electricity.

6. Estimation results & Analysis

In this section I present the parameter estimations for equations (9) and (10) and analyze the results. This is followed by several robustness checks. Finally, I examine what happens to the equilibrium EV sales and number of charging stations in equations (7) and (8) when moving toward compatibility.

Regression results for EV demand

Table 2 (see Appendix) presents the estimated parameters of the EV demand model. Columns a and b present OLS estimates of the model without and with car model fixed effects respectively. Columns c and d contain the IV estimates for models a and b.¹⁹

The estimated parameter for the number of charging stations increases drastically when using instrumental variables and is positive and significant in all permutations of the models. The estimated size of the network effect in column d is 0.408, which is larger than the OLS estimates. Because of the log-log model specification we can interpret this directly as an elasticity, meaning that an increase in the number of compatible charging stations by 10 % is associated with an approximate increase of 4.1 % in the sales of a car model. Given the OLS estimates, this suggests that the number of charging stations is negatively biased due to unobserved shocks in vehicle demand. This may plausibly be due to domestic charging, which is not observed in this framework, and local government incentives such as free charging at commuter parking. The estimated effect is approximately half the magnitude of the 0.844 in the US market as found by Li et al. (2017). This could reflect the smaller networks created through incompatibility although since incompatibility is present in the US as well, I believe the lower effect is due to Sweden's higher levels of domestic charging. Moreover, Springel (2016) finds EV demand network elasticities of approximately 0.4 using a similar framework. The Norwegian market is considered comparable to the Swedish market (Naturvårdsverket sometimes uses Norwegian data for analysis) and one would expect similar magnitudes when comparing markets. However, the Norwegian EV market is largely characterized by second car usage (households using EVs as a secondary transportation option) leading me to suspect

¹⁹ My preferred model is in column d, whose parameters I will use for simulation purposes.

that my estimated network effect is slightly below it's true value (Holtsmark & Skonhoft (2014)).

The estimated parameter for price varies in both sign and significance across different model specifications. When introducing instruments into the models, the price elasticity increases in absolute value and for model d the price elasticity entails that a 1 % increase in price is associated with a 1.3 % decrease in demand. The price elasticity is not significant when controlling for model fixed effects. This could stem from consumer unobservables such as brand premiums as well as the high proportion of early adopters.

This price elasticity is lower than that of other empirical work on car markets but is in line with studies of EV markets. For example, Li et al (2017) finds a price elasticity of approximately -1.3 for the EV market in the US. Moreover, electric vehicle owners tend to have higher incomes, be less price sensitive, as well as electric vehicles being subsidized, meaning we do not observe what would happen in the absence of the subsidies. In addition, as mentioned electric car owners tend to be early adopters and environmentally conscious consumers. For these the price may be less important than the perceived environmental benefits to the alternative. Owning an EV can itself be a statement (Holtsmark & Skonhoft 2014, Kahn 2007). The BEV estimate is negative in all model specifications and a BEVs decrease overall demand by approximately 1 %, most likely due to the fact that $\frac{3}{4}$ of the Swedish EV fleet is made up of PHEV. An additional potential source of advantages for EVs is that of lower fuel costs. All else held constant, an increase in gasoline prices should increase EV adoption through increased fuel savings. In all specifications, the estimates are negative and significant (except for column a).²⁰ This suggests that increasing gasoline prices lead to lower rates of EV adoption. This is unlikely, and I believe the negative effect is a function of the coincidental decrease in fuel costs since 2014 and the rapid increase in EV sales during the same period.

Moreover, both mean income and population density have positive effects on EV demand. The effect of mean income is in line with the idea of lower price sensitivity of EV owners. The effect of population density could be a factor of congestion taxes in larger cities. Average commute time has a negative effect on EV demand likely through range anxiety.

²⁰ In a previous analysis, I included gasoline price interacted with a dummy for BEV giving the same results as the above.

The regression results suggest that there is both a statistically and economically significant impact of the number of compatible charging stations on EV adoption decisions. Using the average price, the effect on vehicle demand of a 1 % increase in the number of compatible stations is equivalent to a price reduction of approximately 17 000 SEK. This suggests that even though the potential and spread of domestic charging is large in Sweden, availability and access to commercial charging stations are important factors for EV adoption. This may stem from ingrained driving behavior as arguably most drivers move from traditional vehicles to EVs rather than be first-time buyers.

To investigate geographic heterogeneity in network effects, I interact the charging stations variable in equation (9) with the most common type of municipality in the county. The type of municipality is an index by Statistics Sweden that groups municipalities into nine categories. I define the county as the municipality type of the municipality in which the most EVs were sold within the county, using metropolitan areas as my baseline. Table 3 shows the variables of interest from this model specification. Including the interactions shows that the network effects are more prominent in metropolitan areas than in other areas. The interaction effects for small (smaller cities) and large (larger cities) are significant and negative respectively. There is a negative relationship between the population and population density and the network effect. This is likely due to more opportunities for domestic charging in less populated areas. Alternatively, this could reflect lower levels of congestion in smaller cities reflecting the increased likelihood of finding a free charging station when needed²¹.

Regression results for charging station deployment

Table 4 (see Appendix) presents the estimation results of the charging station deployment model. As with the EV sales model, I present the model with different specifications. The network effect is positive and significant in all model specifications and is robust across different estimation methods. The value of 0.390 suggests that an increase of 10 % of the number of compatible vehicles is associated with an increase in the number of charging stations by 3.9 %. As the regression coefficient is larger than the OLS for the IV specification, this suggests that the installed EV fleet is negatively correlated with unobserved shocks to charging

²¹ In addition, I estimated equation (9) without the zero market shares which did not qualitatively change the parameter interpretation.

station deployment. This value is smaller than those found in the US. I can think of three possible reasons for this. First, as mentioned above, the level of domestic charging is larger in Sweden than the US whose effect is not fully captured in the data. Second, construction of EV charging stations can be viewed as a form of CSR (corporate social responsibility) which is driven by other factors than the installed base of EVs. Third, the construction of charging stations may be driven by the expectations of future EV sales and thus, in part, grow independently of the EV market. Neither of the EV sales instruments are significant in the charging station model. The approximate cost of construction is measured as the sum of construction costs for different levels of charging using cost estimated from E-Mobility. The variable for cost is negative and significant. As most subsidies for charging station deployment are from the central government these are the same for all counties and enter the equation through the cost term.

Robustness check

The variable for compatible charging stations suffers from bias due to measurement errors in my dataset as each observation for the charging stations only lists one of the available standards. To see whether this affects my results I run a simulation for both markets where I add a random term to the variables of interest to see how robust the model parameters are to changes in the independent variable stemming from measurement errors. As I do not observe the true value for the number of compatible charging stations and the installed base of EVs, I increase the value by a random term so that $\hat{Y} = \hat{B_0} + \hat{B_1}(X + r) + \hat{B_2}Z$. The random term $r \sim U(mean(\mu), max(\mu))$ where μ is a vector of the difference between the total number and the observed number. The true value of the variable lies between the observed and the total and I run the simulations 10 000 times for each equation. Table 5 shows key metrics from the simulations.

When increasing the number of charging stations, the estimated network effect remains qualitatively unchanged, suggesting that the measurement errors do not pose a threat to the conclusion drawn from the EV equation parameters. Moreover, the range of the estimated effects ranges from 0.338 to 0.491, giving the estimated average a range of approximately 20 %. For the charging station equation, the average parameter is again consistent with the initial

model. However, the range of estimates is rather large. Moreover, whereas the EV simulation appears random with a center of mass around the initial estimate, the charging station simulation appears to trend slightly down with lower standard errors for lower values of the parameter estimate. Although there is a center of mass that is consistent with the initial parameter estimate (Figure 5).

Policy simulation

I find positive and significant indirect network effects on both markets generating feedback loops. This has important policy implications regarding the cost effectiveness of subsidies intended to increase the EV adoption rate. To evaluate the impact on the equilibrium values of electric vehicles and charging stations, I use the estimated parameters from the both regressions to show the model implied equilibrium levels in equations (7) and (8) when adjusting the level of compatibility.

Figure 6 shows the equilibrium values for car sales and the number of charging stations under different levels of compatibility. The equilibrium values for both equations show a logarithmic growth path with decreasing returns to scale from increases in the level of compatibility. Using the average car model compatibility $(\frac{\sum_{k=1}^{n} \sum_{i=1}^{n} \psi_{kmt}}{n} = 0.63)$ as a point of comparison, this could increase the steady-state equilibrium of both car sales and charging stations by approximately 1.24 % and 6.65 % respectively²². This implies modest gains to EV adoption rates from compatibility policies. Mandates regarding compatibility could potentially be welfare improving as the network sizes grow and mobility of the users increases, although this must be compared to the cost of redesigning existing charging stations.

7. Conclusion

This thesis aims to show and estimate the indirect network effects on the Swedish market for electric vehicles and market for commercial charging stations. I find an elasticity of the

 $^{^{22}}$ I calculate this by multiplying the percentage increase from adjusting the equilibrium values by the terms $\beta_1^2\gamma_1\ln(0.67)$ and $\gamma_1\ln(0.67)$ and calculate the percentage change. I multiply this by the fraction of the existing base of EVs that are compatible with a level 3 charging standard.

adoption of electric vehicles with regard to charging station availability of 0.41 and an elasticity of charging station deployment with regard to the installed base of compatible electric vehicles of 0.39. The relative magnitude of the effects suggests that subsidies for charging station deployment are only marginally more cost-effective than policies aimed at EV demand. Furthermore, I construct a model that shows that there is a positive logarithmic relationship between the level of compatibility and the steady-state equilibrium car sales and number of charging stations. This study offers insights into policy design for promoting EV adoption. First, the relative size of the indirect network effects suggests that subsidies for charging stations are only marginally more cost-effective than price subsidies for electric vehicles and a mix of policy instruments in likely needed for increased rates of EV adoption. Second, increasing the level of compatibility is potentially welfare improving, although these have to be compared to the one-time cost of rebuilding existing charging stations.

Moreover, the geographic heterogeneity of network effects in equation (9) suggest that optimal policy design should not only consider reaching beyond the inframarginal consumer (as mentioned in the introduction). Optimal policy design should consider local market conditions for EV adoption and subsidies directed to metropolitan areas could be more efficient in terms of both EV adoption as well as reduced externalities (such as noise and air pollution).

In addition, the response to changes in firm incentives from compatibility policies will impact the efficiency and scope for policy action. Due to the nature of ownership of charging stations in Sweden (mainly third party) and the relative small size of the Swedish market, I argue that this will not impact firm behavior in a substantial way. The framework used in this thesis is rather easy to apply to other markets and in markets such as Germany where car manufacturers play a larger role in terms of charging station deployment (Wissenbach & Busvine ,2017), the conclusions drawn may be quite different. As charging standards are decided on by the European Commission, efficient enforcement of compatibility policies must be uniform and coordinated across all member states for optimal results.

8. Suggestions for future research

My market delimitation allows me to limit the number of zero values in the data but loses possibly relevant geographic heterogeneity. For future research I suggest defining each market as a network containing the home municipality and its' neighbors. Further, I do not have data on private or domestic charging stations. To my knowledge, this data is not available at the time of writing but could potentially be addressed through credible proxies. Finally, as the market continues to grow, more data points accumulate, and market conditions may change thus warranting further research.

References

ACEA (European Automobile Manufacturers Association) (2017). *Tax guide 2017*. Retrieved from http://www.acea.be/publications/article/acea-tax-guide.

BBC (2017, November 8). *EU car firms should cut CO₂ emissions by 30 % by 2030*. Retrieved from <u>http://www.bbc.com/news/business-41914805</u>.

Belleflamme, P., & Peitz, M. (2015). *Industrial organization: markets and strategies*. Cambridge University Press.

Beresteanu, A., & Li, S. (2011). Gasoline prices, government support, and the demand for hybrid vehicles in the United States. *International Economic Review*, *52*(1), 161-182.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, 242-262.

Berry, S., Levinsohn, J., & Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica: Journal of the Econometric Society*, 841-890.

Berry, S., Linton, O. B., & Pakes, A. (2004). Limit theorems for estimating the parameters of differentiated product demand systems. *The Review of Economic Studies*, *71*(3), 613-654.

Borenstein, S., & Davis, L. W. (2016). The distributional effects of US clean energy tax credits. *Tax Policy and the Economy*, *30*(1), 191-234.

Chandra, A., Gulati, S., & Kandlikar, M. (2010). Green drivers or free riders? An analysis of tax rebates for hybrid vehicles. *Journal of Environmental Economics and management*, *60*(2), 78-93.

City of Stockholm (2016), "Experiences from setting up public charging facilities for electric vehicles in Stockholm", Stockholm: City of Stockholm.

Diamond, D. (2008). The impact of government incentives for hybrid-electric vehicles: Evidence from US states. *Energy Policy*, *37*(3), 972-983.

Emobility (Energimyndigheten) (2018a). *Om olika kontakter*. Retrieved from http://emobility.se/startsida/laddstationsguiden/forberedelser/om-olika-kontakter/.

Emobility (Energimyndigheten) (2018b). *Laddstationen – er bästa affärer*. Retrieved from http://emobility.se/wp-content/uploads/sites/3/2014/10/Emobility.se-Kommersiella.pdf.

Euractiv (2018). *EU's car emission goals for 2030 stir up 'tech neutrality' debate*. Retrieved from <u>https://www.euractiv.com/section/electric-cars/news/eus-car-emission-goals-for-2030-stir-up-tech-neutrality-debate/</u>.

European Parliament (2013). *Alternative fuel stations: Transport committee backs draft law to expand networks*. Retrieved from <u>http://www.europarl.europa.eu/news/en/press-</u> <u>room/20131125IPR26108/alternative-fuel-stations-transport-meps-back-draft-law-to-expand-</u> <u>networks</u>.

European Commission (2014). 2030 climate & energy framework. Retrieved from https://ec.europa.eu/clima/policies/strategies/2030 en.

Financial Times (2017, November 8). *New EU vehicle emissions rules disappoint climate activists*. Retrieved from <u>https://www.ft.com/content/e075af19-e7b0-3da3-ac84-</u>94bc916a5130.

Gallagher, K. S., & Muehlegger, E. (2011). Giving green to get green? Incentives and consumer adoption of hybrid vehicle technology. *Journal of Environmental Economics and management*, *61*(1), 1-15.

Hidrue, M. K., Parsons, G. R., Kempton, W., & Gardner, M. P. (2011). Willingness to pay for electric vehicles and their attributes. *Resource and Energy Economics*, *33*(3), 686-705.

Holland, S. P., Mansur, E. T., Muller, N. Z., & Yates, A. J. (2016). *Distributional effects of air pollution from electric vehicle adoption* (No. w22862). National Bureau of Economic Research.

Holtsmark, B., & Skonhoft, A. (2014). The Norwegian support and subsidy policy of electric cars. Should it be adopted by other countries?. *Environmental science & policy*, *42*, 160-168.

Houde, J. F. (2012). Spatial differentiation and vertical mergers in retail markets for gasoline. *American Economic Review*, *102*(5), 2147-82.

Huse, C., & Lucinda, C. (2014). The market impact and the cost of environmental policy: evidence from the Swedish green car rebate. *The Economic Journal*, *124*(578). (IEA, 2018).

Ishii, J. (2008). Compatibility, competition, and investment in network industries: ATM networks in the banking industry. *Stanford University WP*.

Kahn, Matthew. (2007). Do greens drive Hummers of hybrids? Environmental ideology as a determinant of consumer choice. *Journal of Environmental Economics and Management*, 54(2), 129-45.

Katz, M. L., & Shapiro, C. (1985). Network externalities, competition, and compatibility. *The American economic review*, *75*(3), 424-440.

Knittel, C. R., & Stango, V. (2008). Incompatibility, product attributes and consumer welfare: evidence from ATMs. *The BE Journal of Economic Analysis & Policy*, 8(1).

Knittel, C. R., & Stango, V. (2011). Strategic incompatibility in ATM markets. *Journal of Banking & Finance*, *35*(10), 2627-2636.

Lee, R. S. (2013). Vertical integration and exclusivity in platform and two-sided markets. *American Economic Review*, *103*(7), 2960-3000.

Li, S., Tong, L., Xing, J., & Zhou, Y. (2017). The market for electric vehicles: indirect network effects and policy design. *Journal of the Association of Environmental and Resource Economists*, *4*(1), 89-133.

Li, J. (2017). *Compatibility and Investment in the US Electric Vehicle Market*. Working paper. Cambridge, MA: Harvard University, Department of Economics.

McFadden, D. L. (1974, June). Conditional Logit Analysis of Qualitative Choice Behavior. In P. Zarembka (Ed.), Frontiers in Econometrics, pp. 105–142. New York: Academic Press.

Michalek, J. J., Chester, M., Jaramillo, P., Samaras, C., Shiau, C. S. N., & Lave, L. B. (2011). Valuation of plug-in vehicle life-cycle air emissions and oil displacement benefits. *Proceedings of the National Academy of Sciences*, *108*(40), 16554-16558.

Naturvårdsverket (2017). *Resultat för Klimatklivet*. Retrieved from <u>http://www.naturvardsverket.se/Stod-i-miljoarbetet/Bidrag/Klimatklivet/Resultat-for-</u> Klimatklivet/.

Nordlund, A., Granström, R., Hillman, K., & Zampoukos, K. (2017). Användarnas beteende och syn på laddbara bilar: Rapport från projektet SELF-i.

Petrin, A. (2002). Quantifying the Benefits of New Products: The Case of the Minivan. Journal of Political Economy 110(4), 705–729.

Power Circle. (2018). ELIS 2.0.3 - 2017-12-31. Stockholm. Power Circle.

SCB (2016). *Totala utsläpp och upptag av växthusgaser efter växthusgas och sektor*. Retrieved from

http://www.statistikdatabasen.scb.se/pxweb/sv/ssd/START_MI_MI0107/TotaltUtslappN/table/table ViewLayout1/?rxid=f45f90b6-7345-4877-ba25-9b43e6c6e299.

Small, K. A. and H. S. Rosen (1981). Applied Welfare Economics with Discrete Choice Models. Econometrica 49(1), 105–130.

Springel, K. (2016). Network Externality and Subsidy Structure in Two-Sided Markets: Evidence from Electric Vehicle Incentives. *Berkeley: University of California*.

Trafa (2017). *The Swedish national travel survey 2015-2016*. Retrieved from https://www.trafa.se/globalassets/statistik/resvanor/2016/rvu_sverige_2016-reviderad-7-juli.pdf.

Transportstyrelsen (2018). *Frågor och svar om supermiljöbilspremien*. Retrieved from <u>https://transportstyrelsen.se/sv/vagtrafik/Miljo/Klimat/Miljobilar1/supermiljobilspremie1/</u>.

United States of America, Appellee v. Microsoft Corporation, Appellant, 253 F.3d 34 (D.C. Cir. 2001)

Williams, H. C. W. L. (1977). On the Formation of Travel Demand Models and Economic Evaluation Measures of User Benefit. Environment and Planning 9, 285–344.

Wissenbach, I. & Busvine, D. (2017, Nov). German carmakers team up to launch pan-European electric car charging network. *The Independent*. Retrieved from https://www.independent.co.uk/news/business/news/german-carmakers-bmw-daimer-fordvolkswagen-audi-porsche-european-network-charging-stations-a8035001.html.

Zivin, J. S. G., Kotchen, M. J., & Mansur, E. T. (2014). Spatial and temporal heterogeneity of marginal emissions: Implications for electric cars and other electricity-shifting policies. *Journal of Economic Behavior & Organization*, *107*, 248-268.

Appendix



Figure 2





Figure 4



Source: Chargex (2018); GADM (2018).





Table 1

Variable	Mean	\mathbf{SD}
Sales of EV model	14.34	85.44
No. of compatible charging stations	50.83	51.15
Total no. of charging stations	84.82	92.45
MRSP - tax incentives	12.49	0.95
No. grocery stores	316.90	343.01
Mean income (county)	256.60	27.39
Population density	310.21	803.53
Gasoline price	14.04	0.67
Average commuting distance	26.86	2.70
Avg. temperature in January	-3.30	4.61
No. of charging station _{$t-1$}	1189.37	604.93
No. of observations	3192	
No. of compatible charging stations	17.94	38.94
Total no. of charging stations	67.75	82.09
Avg. temperature in January	-3.31	4.39
Avg. temperature in $January_{t-1}$	-4.04	4.70
Gasoline price	13.93	0.86
Gasoline $\operatorname{price}_{t-1}$	13.93	0.68
No. of compatible electric vehicles	258.64	1206.34
Total no. of electric vehicles	694.47	2272.30
No. grocery stores	326.21	352.09
No. gas stations	161.95	112.41
Cost of construction	12.62	0.966
No. of observations	489	

Table 2

Variable	a OLS	b OLS	с IV	d IV
ln(No. of comp. charging stations)	0.161***	0.105***	0.793***	0.408***
	(6.07)	(5.01)	(16.85)	(6.25)
ln(MRSP-tax incentives)	-0.101***	0.728^{***}	-0.923***	-1.331
	(-3.33)	(5.41)	(-17.75)	(-0.62)
BEV	-0.297^{***}	-0.796***	-1.197^{***}	-0.931^{***}
	(-4.67)	(-4.30)	(-13.39)	(-3.33)
ln(Mean income)	2.262^{***}	1.515^{***}	0.567	0.800***
	(7.14)	(6.47)	(1.57)	(2.84)
ln(Population density)	-0.125^{***}	0.103^{***}	-0.0958**	0.114^{***}
	(-4.91)	(4.81)	(-3.05)	5.11)
ln(Gasoline price)	-0.719	-2.609***	-1.515^{**}	-3.922***
	(-1.55)	(-7.37)	(-2.71)	(-6.10)
ln(Avg. January temperature)	4.910^{***}	1.036	0.494	-1.293
	(4.18)	(1.24)	(0.34)	(-1.10)
ln(Avg. commute time)	-3.241^{***}	-2.139^{***}	-1.665***	-1.346***
	(-10.71)	(-8.94)	(-5.09)	(-4.65)
Constant	-25.00***	-8.955**	14.31	33.90
	(-3.49)	(-1.66)	(1.58)	(1.06)
N	3192	3192	3192	3192
Model FE	No	Yes	No	Yes
Overidentification test			1000000000	22.50.020.04
Hansen J statistic			72.75	26.04
			(0.00)	(0.00)

Dependent variable: ln(Sales of Model)

 $^{***}p < 0.01, \, ^{**}p < 0.05, \, ^*p < 0.1$

Standard errors: White Robust Standard Errors. Z-value reported in parentheses.

Table 3

Variable	d
ln(No. of comp. charging stations)	0.53***
\times small	(7.27) -0.44***
\times large	(-4.33) -0.14**
ln(MRSP-tax incentives)	(-2.00) -1.14
N	(-0.73)
Model FE	Yes
Overidentification test	89.207
Hansen J statistic	(0.00)

Dependent variable: ln(sales of model)

 $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Standard errors: White Robust Standard Errors. Z-value reported in parentheses.

Table 4

Dependent variable: ln(no. compatible charging stations)

Variable	a OLS	b IV
ln(No. of compatible EV)	0.304***	0.390***
and a second contraction of the second contraction of	(7.35)	(3.08)
$\ln(\text{No. of grocery stores} \times \text{national stations}_{t-1})$	0.0785**	0.0572
	(2.61)	(1.33)
$\ln(\text{No. of gas stations} \times \text{national stations}_{t-1})$	-0.0428	-0.0402
	(-1.42)	(-1.32)
ln(approx. cost of construction)	-0.0836***	-0.767***
	(-15.83)	(-6.60)
Constant	9.657***	9.135***
	(14.10)	(8.78)
N	489	489
Overidentification test		
Hansen J statistic		0.055(0.814)

 ${}^{***}p < 0.01, {}^{**}p < 0.05, {}^{*}p < 0.1$

Standard errors: White Robust Standard Errors. Z-value reported in parentheses.

Table 5

Simulation output

	Mean	\mathbf{SE}	Min.	Max.
$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 (X+r) + \hat{\beta}_2 \mathbf{Z}$	0.408	0.019	0.338	0.491
$\hat{X} = \hat{\gamma_0} + \hat{\gamma_1}(Y+r) + \hat{\gamma_2}\mathbf{P}$	0.390	0.071	0.234	0.942