Indirect network effects and policy implications: empirical analysis of the Chinese electric vehicle market

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Abstract

Governments can accelerate technology adoption by directly subsidizing a technology or subsidizing the adoption of its complements when indirect network effects exist. The optimal policy choices depend on the scale of indirect network effects relative to direct policy effects.Using data on electric vehicle (EV) sales and charger numbers in China, this paper estimates the mutual indirect network effects between EV adoption and charging station infrastructure and assesses the effectiveness and efficiency of EV purchase subsidies and charger subsidies on EV adoption. Although the indirect network effect of chargers on EV adoption is significant,our findings suggest that EV purchase subsidies are 34.4% more effective than equally budgeted charger subsidies in promoting EV adoption at a low cost of efficiency loss. Moreover, these two subsidies have different effects on the distributions of EV sales and consumer welfare:the recent changes in EV subsidies favor high-range vehicles and their buyers, while charger subsidies favor low-range vehicles and their buyers.

Keywords: Indirect network effect; subsidy; Chinese automobile market; welfare analysis

JEL Classification: H23, D61, L62

1 Introduction

Many countries have endeavored to accelerate the adoption of electric vehicles (EVs) to ameliorate the negative externalities, especially emission pollution, of vehicle consumption. However, the adoption rates of EVs are still low in most countries. Two issues have impeded the mass market adoption of EVs: high ownership costs and limited charging infrastructure availability (Meunier and Ponssard, 2020). To combat the first issue, governments worldwide have introduced various incentive programs to subsidize EV consumption (Springel, 2020; Beresteanu and Li, 2011; DeShazo et al., 2017; Li et al., 2017; Axsen and Wolinetz, 2018). To combat the second issue, countries have issued subsides on charging infrastructure (Greene et al., 2020), especially when they believe that private investment in charging stations is lower than socially optimal (Yu et al., 2016).

Previous studies have compared the effectiveness of alternative policies, including reducing EV ownership costs and stimulating investment in charging infrastructures, on EV adoption and the environment (Li et al., 2017; Springel, 2020; Meunier and Ponssard, 2020; Bonges and Lusk, 2016; Shi et al., 2020; Zhu et al., 2019). In particular, Li et al. (2017) and Springel (2020) suggest that compared to high ownership costs of EV, consumers in their respective circumstances (i.e., the US market in 2011-2013 in Li et al. (2017) and the Norway market in 2010-2015 in Springel (2020)) are more concerned with charging infrastructure availability. Consumers have range anxiety, that is, the fear that a vehicle has insufficient range to reach its destination; therefore, the indirect network effect of charging stations plays a significant role in EV adoption. Consequently, both studies found that station subsidies were more than twice as effective as car purchase subsidies in promoting EV adoption. However, their conclusions may depend on socioeconomic factors, such as consumers' price (EV subsidy) sensitivity, the size of the charging station network, and vehicle features (such as driving range),[1] which often exhibit cross-market or temporal variations. Hence, their conclusions may not be extended to a general context. Moreover, the indirect network effects could be heterogeneous over products of different quality and varying over markets of different infrastructure conditions. Therefore, the relative efficiency of the two subsidy policies may change as technology evolves and the distribution of product quality changes significantly in this dynamic industry.

Considering the dynamic nature of the EV industry, therefore, it is very important to determine whether the policy implications suggested by these previous works are applicable to different development stages of the industry or in different socioeconomic circumstances. Currently, for example, China has the largest network of charging stations worldwide, and most EVs currently have much longer ranges than they had previously; however, Chinese consumers are more price sensitive, as their income is much lower than that documented in previous studies by, for example, Li et al. (2017); Springel (2020). Therefore, the substitutability between EVs and station subsidies could be quite different from what has been documented by previous literature (Meunier and Ponssard, 2020; Bonges and Lusk, 2016; Li et al., 2017; Springel, 2020). Empirical evidence particular to this globally dominant EV market has crucial managerial and policy implications. EV manufacturers will benefit from such quantitative studies since a significant, if not the largest, share of their profits is obtained from this market; thus, they are keen to learn the impact of policy on their sales. The government is also concerned with the impact of alternative policies, especially the impact on EV technology distribution and its future progress, since alternative policies may guide the development of the EV industry in different directions.

This paper studies the key determinants of EV adoption and the supply of charging infrastructure, revisiting the indirect network effects between EV demand and charging infrastructure supply when EV

[1] For example, as pointed out by Li et al. (2017), their findings are attributed mainly to the fact that early EV adopters were insensitive to prices but were highly concerned with the low driving ranges of EVs.

quality has been improved significantly and the charger network has been developed to some extent. More importantly, we investigate the heterogeneity of the indirect network effects of charging infrastructure on the adoption of EVs with different technological features and the heterogeneous welfare effects of alternative subsidy policies on consumers of differentiated EVs. Using EV sales and the number of chargers in the Chinese market over 2016-2019, we estimate the functions of both EV demand and the size of the charger network. We use an instrumental variable unique to the Chinese market to identify the causal effects of charger networks on EV sales and use the gasoline price as an instrumental variable to identify the causal effects of the installed base of EVs on charger investment, deploying the variation in EV sales, government subsidies and charger networks across provinces. Furthermore, we conduct a counterfactual analysis using the estimated demand and charger network function to examine the effectiveness of EV and station subsidies on EV adoption and assess their welfare effects.

Our empirical findings suggest that EV purchase subsidies are more effective in stimulating EV adoption than equally budgeted subsidies on chargers in China, which is opposite to the findings in the previous literature (Li et al., 2017; Springel, 2020). The reason is that our estimation suggests Chinese consumers are more sensitive to EV prices and subsidies than consumers in developed nations (*e.g.*, Li et al., 2017; Springel, 2020),[2] while the indirect network effect of charging infrastructure is lower. Correspondingly, the substitutability between station subsidies and EV subsidies in promoting EV adoption is opposite to the findings in Li et al. (2017) and Springel (2020). The reverse conclusions on the effectiveness of EV and station subsidies on EV adoption can be attributed to the lower income (Li, 2017) and larger charger network in China as well as upgraded battery technology, which has significantly lengthened the EV driving ranges and therefore notably alleviated consumers' range anxiety.

Our analysis also indicates that significant heterogeneity of indirect network effects exists, with lower-range EVs being more sensitive to charging infrastructure than higher-range models. Such heterogeneity is crucial in that it makes the distributional effects of charger subsidies different from those of EV subsidies: charger subsidies favor low-range EVs, while EV subsidies favor targeted EVs of different ranges. Hence, EV subsidies can serve as a better policy instrument to promote technology adoption. Accordingly, EV subsidies are more cost effective than charger subsidies in the sense that the gain in consumer surplus net of externalities is higher under EV subsidies than under charger subsidies with an equal budget size. Intuitively, this is because charger subsidies fail to leverage the heterogeneity of indirect network effects and therefore are unable to generate the same welfare effect on high-range EVs as they do on low-range EVs. In essence, our findings have the same policy implications as those proposed by DeShazo et al. (2017), who suggest that policies can leverage heterogeneity across products to improve policy performance.

This paper contributes to the literature in the following aspects. First, this paper extends previous studies on indirect network effects (*e.g.,* Chou and Shy, 1990; Clements and Ohashi, 2005; Gandal et al., 2000; Katz and Shapiro, 1994), especially the literature on the indirect network effects of transportation infrastructure on vehicle adoption (*e.g.*, Shriver, 2015; Li et al., 2017; Springel, 2020; Zhou and Li, 2018), by examining the heterogeneity of such effects. In particular, this paper investigates the heterogeneous indirect network effects of charging infrastructure on EVs with different characteristics (particularly, driving range) and the heterogeneous welfare effects of government policies on the consumers of these differentiated EVs. Indirect network effects of charger infrastructure on EV adoption arise due to complementarities between EVs and chargers. However, EVs' reliance on chargers varies according to their driving ranges, leading to heterogeneity of the charger infrastructure's indirect network effects on EV adoption. This implies that the effectiveness of subsidies on charging infrastructure could vary depending on the EV

[2]This is consistent with previous literature (*e.g.*, Li, 2017) about the difference in price sensitivities for the traditional gas-fuelled vehicles between the Chinese and American consumers.

range. Similarly, EV subsidies could have heterogeneous effects on EVs of different prices. Therefore, EV and infrastructure subsidies may result in different sales distributions of EVs, leading future technology improvements in different directions. EV manufacturers and social planners are interested in whether these effects exist and, if so, how alternative subsidies might accelerate the adoption of EVs with different qualities and distribute the benefits of subsidies among EV consumers.

Second, our study adds to the emerging literature on the effectiveness of various incentive policies on EV adoption. Owing to EVs' potential to reduce the impact of transportation on climate change and other environmental issues, governments have been employing incentives to increase EV adoption. Recent empirical studies have assessed and compared the effectiveness of alternative policies; however, no unanimous conclusions have been reached on either the effectiveness or the optimality of these policies. Münzel et al. (2019) indicate that financial incentives have an impact on plug-in EV (PEV) sales and thus can facilitate their diffusion. Similarly, Axsen and Wolinetz (2018) suggest that purchase incentives play a significant role in reaching the long-term goal of EV adoption in Canada. Azarafshar and Vermeulen (2020) suggest that approximately 35% of EV sales are attributed to purchase incentives. Quite a few studies, on the other hand, have emphasized the importance of the indirect network of charging infrastructure and thus the impact of station subsidies on EV adoption. Greene et al. (2020), for example, suggest that public charging infrastructure has tangible and intangible value, such as reducing range anxiety (Meunier and Ponssard, 2020) or building confidence in the future of the PEV market, while Springel (2020) and Li et al. (2017) quantify station subsidies to be more than twice as effective as EV subsidies. However, some studies (*e.g.*, Carley et al., 2019) argue that the current suite of policies is not as effective as it could be and is potentially more expensive than it needs to be. Using panel data on EV sales and charging stations across US Metropolitan Statistical Areas (MSAs), Zhou and Li (2018) find that more than half of MSAs face critical mass constraints on EV adoption; therefore, a subsidy policy targeting these critical-mass constrained MSAs could be much more effective in promoting EV adoption than the current uniform policy. These diverse conclusions, conditional on their respective research environment, suggest that a study on the policies of the Chinese market, the largest EV market worldwide, is imperative, especially when the effectiveness of these policies is still unknown.

Third, our paper presents the first study on the mutual indirect network effects between EVs and charging stations in a developing economy with a highly centralized government. At least two salient features of the Chinese market make our empirical results distinct from those obtained from analyses on developed economies in the literature: 1) the central government plays a powerful role in economic activities and has committed many resources to the development of both EV technology and charging infrastructure, making EVs a world-leading industry. The government frequently adjusts its incentive policies for EV adoption and infrastructure investment. 2) Economic growth is unbalanced across markets. The sizes of infrastructure networks and consumers' preferences are quite different across markets, so local governments adopt different types and scales of incentives to promote EV adoption. On the one hand, these two features imply significant variation in the key factors shifting demand for EVs and the supply of chargers, rendering our model identification more efficient. On the other hand, these features also command a robust analysis framework capable of assessing and predicting the effects of dynamic policies. To the best of our knowledge, no such framework tailored for the Chinese market has been developed to date, and therefore, this paper aims to fill this vacancy.

Finally, this paper also estimates the subsidy effects on the externalities of EV consumption, considering China's current electricity generation methods and notable transition towards clean energy. Holland et al. (2016) find considerable heterogeneity in the environmental benefits of EV adoption depending on the different fuel mixes for generating electricity across regions in the US. Currently, most electricity power

is not generated using clean resources in China,[3] which makes the environmental effects of EVs in China quite different from those in previous studies on developed economies such as Norway (Springel, 2020). This makes externality a crucial component of welfare analysis. The inclusion of externalities in welfare analysis changes the conclusions on the efficiency analysis of alternative policies. However, China's power generation has been undergoing an unprecedented transition from coal firing to renewable energy sources. The share of coal firing power generation dropped from 78% in 2010 to 64.6% in 2019.[4] We predict that this transition will render EV subsidies more cost effective.

The rest of the paper is organized as follows. Section 2 introduces the institutional background of our study, including the markets for EVs and stations and pertinent government policies. Section 3 explains our empirical model and discusses the identification issues. Section 4 describes the data. Section 5 presents our empirical findings from the model estimation. Section 6 demonstrates the design and results of the counterfactual analysis, elaborating on the effectiveness and welfare impact of alternative government policies. Finally, section 7 concludes the paper.

2 Institutional background

2.1 Industrial structure

2.1.1 Electric vehicles

The Chinese EV industry has been developed with the government support from its inception. The Auto Industry Development Policy (published in 2004) clarified the government's role in promoting the development of EV industry as follows.

> The automotive industry shall, in combination with the requirements of the strategy of state energy source structural adjustment and emission standards, positively carry out research and industrialization of such new types of power as the electric cars, batteries used as vehicles power, etc., and focus on the development of hybrid vehicle technology and diesel motor technology for cars. The state shall take measures in such aspects as the scientific and technological research, technological transformation, industrialization of new technologies, and policies and environments, etc., to promote the production and use of the hybrid power vehicles.

That year, sixteen Chinese state-owned companies formed an electric vehicle industry association in Beijing, whose goal was to integrate technological standards and create a information-exchange mechanism among the members to develop the EV industry. In 2007 China invested over RMB 2 billion (US$300 million) in new energy vehicle development.

Most of the leading Chinese EV manufacturers have experience in the production of internal combustion engine vehicles (ICEVs; *e.g.,* Beijing New Energy Automobile Co. Ltd., BYD, Geely, Chery and Roewe), while some entrants specialize in designing and developing electric vehicles only (*e.g.,* NIO and Leapmotor). While the ICEV industry is highly competitive (Hu et al., 2014), the EV industry is relatively more concentrated as shown in Table 1a. However, as more and more ICEV manufacturers started to introduce their EVs and new firms entered this industry, the EV industry has been becoming more competitive over the last a few years (Table 1b). Most Chinese indigenous manufacturers (*e.g.,* Geely and Chery)

[3] In 2019, approximately 64.6% of the power was generated by coal firing, according to "electricity generation by source, People's Republic of China 1990-2019" by the International Energy Agency (IEA, Retrieved 17 October 2020).

[4] IEA Key World Energy Statistics 2011-2020.

produce low-end compact vehicles, while joint ventures (*e.g.,* Toyota-Guangzhou) or foreign-owned enterprises (*e.g.,* Tesla) produce SUVs or upscale sedans.

Figure 1 presents the numbers of EV manufacturers and models at the nameplate level with average monthly sales of no less than 10 and EV price ranges in the Chinese market during 2016-2019. This figure suggests that this market has become more competitive as the numbers of both manufacturers and products have increased over time, which may have contributed to the gradual decline of vehicle prices over years. Meanwhile, Figure 1c suggests that the maximum travel range of EVs increased over the sample period.

2.1.2 Charging stations

EV charging stations emerged alongside the EV industry. In May 2014, State Grid officially removed the regulation on charging infrastructure investment and invited private capital to participate in the construction of electric vehicle charging and power-swapping facilities.[5] Firms responded to this policy change immediately and entered this market to seize a first-mover advantage. Table 2 presents the establishment times of the leading firms in this industry. Except for State Grid and Potevio, which are state-owned enterprises, all the other leading firms were established once this market was open to private enterprises. On December 28, 2015, the central government published 5 national standards for electric vehicle charging interfaces and communication protocols to ensure that the charging networks were compatible with EVs in the market. These standards make the stations of different firms homogeneous products from the perspective of EV drivers. Since then, the network of chargers has been steadily expanding over years (Figure 2).

This industry is concentrated. By October 2020, 667,000 chargers existed, of which direct-current (DC) charging stations and alternative-current (AC) charging stations numbered 291,000 and 376,000, respectively. There were 26 enterprises above a designated size of 1,000 chargers nationally, which accounts for 99.4% of the national total (see Table A-1 for details). The top three operators, Teld New Energy, Star Charge and State Grid, together operated 470,000, representing 70.6% of the total, while Teld alone accounted for 26.0% of the total. Unlike those in the EV manufacturing industry, most firms in the charging station industry are indigenous brands. The top three firms have already diffused into all provinces in China, but the rest of the firms only operate stations in particular areas.

The entry costs of charging stations depend on the type (AC or DC), number and output power of chargers and many other factors, such as land rental costs. Following a report by the China Southern Power Grid, the average investment in each charger is approximately RMB 128,260.[6]

2.2 Policies

Subsidies have played an important role in boosting the adoption of EVs in the Chinese market. The central government first subsidized EV purchases directly. Local governments also provided supplementary subsidies on EV purchases, generating variation in EV ownership costs across cities. Subsidies are set based on EV technical characteristics (range). Table 3 shows the subsidy scheme of the central government and

[5] Opinions on Providing Services of Electricity Supply to and Reporting Installation of Electric Vehicle Charging and Swap Facilities, State Grid, May 27, 2014.

[6] From March until October 2019, this company invested RMB 3.184 billion in station construction and operation. It established 23,000 chargers, which supplied 0.39 billion kWh of electricity. According to State Grid, the average price of electricity in Southern China's provinces is approximately RMB 0.6/kWh. Therefore, the expense on the electricity supply to charger infrastructure has amounted to roughly RMB 0.234 billion, and thus, the total charging infrastructural investment is RMB 2.95 billion; thus, the average investment per charger is approximately RMB 128,260.

the number of EVs eligible for these subsidies. It can be observed that the central government has generally downgraded the subsidies over the years, with the exception of the high-range categories, generating temporal variation in vehicle ownership costs. This policy change may explain the observed trend in vehicle range, as shown in Figure 1c, suggesting a distribution effect of EV subsidies on technology adoption. Unlike the subsidies that are directly provided to consumers through tax credits or rebates in the US and European markets, the subsidies from the Chinese central government are transferred to manufacturers directly;[7] Therefore, when manufacturers set their manufacturer-suggested retail prices (MSRPs), they have already taken the subsidies into consideration. In other words, the MSRPs are central-subsidy-inclusive prices.[8] Local governments could also grant additional EV purchase subsidies, which are directly provided to consumers. Therefore, the net prices consumers have to pay for ownership are the MSRPs net of local subsidies.

While downgrading vehicle subsidies, the central and local governments started to subsidize investment in charging infrastructure. Two types of infrastructure subsidies were granted: subsidies on the construction of charging stations and those on their operation. Since construction subsidies account for the majority of infrastructure subsidies, we focus on policies pertinent to this type only. The schemes of construction subsidies vary across local governments: some governments set subsidies based on the power capacity and type (AC or DC) of charger, subject to a cap per charger or station, while the others grant lump-sum subsidies, regardless of the charger characteristics. For example, on May 25, 2015, Guangdong Province began to subsidize charging stations by providing a lump-sum subsidy of 30% of the construction investment on chargers, subject to caps of RMB 120,000 or 6,000 per DC or AC charger, respectively, and a cap of RMB 0.9 million per station. Later, it changed the subsidy basis to charger power capacity. It subsidized RMB 30 or RMB 6 on DC or AC chargers, respectively, for each kW of charger capacity beginning on January 25, 2018. Therefore, the eventual subsidies depend on the characteristics of each station, such as the number and type of chargers and the construction costs of chargers. As local governments apply different subsidies and adjust the subsidy levels over time, both cross-sectional and longitudinal variation in subsides on EV charging infrastructures is observed in this market.

3 Empirical model and identification

To assess the effects of different subsidies on EV adoption, considering the mutual indirect network effects between EVs and charging stations, we first model both vehicle demand and equilibrium station numbers.

3.1 Vehicle demand

We use a discrete choice model to analyze EV demand. Consider a representative consumer who chooses a vehicle to maximize his utility. The indirect utility of choosing product j from a choice set $A_{mt} = \{1,2,...J_{mt}\}$, where J_{mt} is the number of products in market m at time t, is given by

$$u_{jmt} = \tau_j - \theta_e e_{jmt} + \theta_C C\{R_j\} \times log(N^c_{mt}) + \theta_g gp_{mt} \times FE_j + \xi_{jmt} + \tau_m + \tau_t + \varepsilon_{jmt} \quad (1)$$

[7]Manufacturers have to report sales to the government to settle the transfers once a year.

[8]The manufacturers could strategically determine whether they partially or fully pass the subsidies to consumers. Existing studies on related programs suggest that full pass-through is a reasonable assumption for alternative fuel vehicle subsidies. For example, Muehlegger and Rapson (2018) find a 100 percent pass-through of EV subsidies in California. For hybrid vehicle subsidies, Gulati et al. (2017) find a pass-through close to 80-90 percent, and Sallee (2011) finds that both federal and state tax incentives were fully captured by consumers. As China has been tightening the corporate average fuel economy limits, manufacturers need to fulfill increasingly stringent fuel economy regulations and are incentivized to set the prices of EVs low enough to increase the weights of zero-emission vehicles. Therefore, it is reasonable to assume a full pass-through of subsidies in this study.

where τ_j is the fixed effect of vehicle j, which captures vehicle features that are market- and time-invariant.[9] e_{jmt} is the expense of vehicle ownership, including vehicle prices and applicable license quota fees[10] net of purchase subsidies. The full utility of EVs depends on the availability of charging infrastructure, which is defined as the indirect network effects of chargers on EVs in the literature (*e.g.,* Li et al., 2017; Springel, 2020; Meunier and Ponssard, 2020; Zhou and Li, 2018). This dependence varies in vehicle travel ranges: vehicles with higher ranges are less dependent on the network of chargers. Therefore, we also include the interaction term of vehicle range category $C\{R_j\}$ and the installed base of chargers N^c_{mt} in the model.[11] The utility from buying an EV depends on the operation costs of conventional vehicles, which are the major outside options for EV purchases. When the gasoline price increases, the utility of EVs increases accordingly since they can save more operation costs than ICEVs. In particular, consumers who would have purchased fuel-consuming ICEVs such as large sedans or SUVs become more likely to switch to EVs with similar utilities. Such EVs usually have lower fuel efficiency due to their large size; hence, gasoline prices have disproportionately higher effects on EV models with lower fuel economy. Accordingly, we include an interaction of $gp_{mt} \times FE_j$ in the utility function, where gp_{mt} is the gasoline price in market m at time t, and FE_j is the fuel economy of vehicle j, measured by the electricity consumption per unit of travel distance.[12] We expect that utility increases in this interaction term. ξ is the product characteristics observable to consumers but unobservable to researchers, which may include minor product characteristics that are unobserved in our data. We assume this variable is stochastic, following a distribution with a mean of zero. The two fixed effects, τ_m and τ_t, measure the market and time effects, respectively. Finally, ε is consumers' idiosyncratic taste for a specific model. We assume that this preference follows a type I extreme value distribution.

Consumers may also choose an outside option, which covers the choices of a vehicle model unobservable to the researcher (*e.g.,* an ICEV) or nonpurchase. The utility of this outside option depends on the network of charging stations. As the availability of charging stations decreases, the outside option becomes more attractive due to range anxiety. Therefore, the utility of the outside option is given by

$$u_{omt} = \theta_N log(N^c_{mt}) + \varepsilon_{omt}$$

Following the distribution assumption of ε, the purchase incidence of product j or outside option o has a closed form. Denoting the total value of all the terms other than ε_{jmt} of u_{jmt} in equation 1 by δ_{jmt}, the purchase incidence is formally given by

$$s_{jmt} = \frac{exp(\delta_{jmt})}{\sum_k exp(\delta_{kmt})} \quad \text{and} \quad s_{omt} = \frac{exp(\delta_{omt})}{\sum_k exp(\delta_{kmt})}, \; k = o, 1, 2 ... J_{mt} \tag{2}$$

3.2 Charger supply

The size of the charger network is endogenous. It depends on the subsidies on charging infrastructure and the fleet size of EVs in each market. Following Clements and Ohashi (2005),[13] the number of chargers is

[9] Once the product quality is upgraded, the product is labeled as a new product.

[10] Xiao et al. (2017) lists cities with license quota fees and discusses the working mechanisms of the license quota system in China.

[11] Ideally, the distribution of stations serves as a better measure for the availability of charging infrastructure. We use the number of chargers, subject to data availability.

[12] Because PHEVs and EVs rely in whole or part on electric power, their fuel economy is measured differently than that of conventional vehicles. Miles per gallon of gasoline equivalent (MPGe) and kilowatt hours (kWh) per 100 kilometers (km) are common metrics. The higher the MPGe (lower the kWh/100 km) is, the higher the fuel economy.

[13] they suggested that our current charger supply function could be derived with the assumptions of CES demand and symmetric Bertrand competition among homogeneous firms on the supply side.

given as follows.

$$N^c_{mt} = A(SC^c_{mt})(N^{EV}_{mt})^{\alpha_N} exp(\mu_{mt}) \tag{3}$$

where N^c_{mt} is the cumulative supply of charging infrastructure, which equals the sum of numbers of entry and survival chargers net of the number of exit chargers. SC^c_{mt} is the historical profile of subsidies on charger investment in market m by time t. Its effect on charger supply is captured by function $A(\cdot)$, which attaches different weights to subsidies in different periods up to time t. N^{EV}_{mt} is the EV fleet size in market m by time t given by

$$N^{EV}_{mt} = Q_m \sum_{k=1}^{t} \sum_{j=1}^{J_m} s_{jmk} \tag{4}$$

where Q_m is the size of market m.

Specifying $A(\cdot)$ to be a power function with a coefficient of α_{sc} and taking the logarithmic transformation on equation 3, we use the following empirical model to identify the parameters in the charger supply equation:

$$log(N^c_{mt}) = \alpha_{sc} log(SC^c_{mt}) + \alpha_N log(N^{EV}_{mt}) + \tau_m + \tau_t + \mu_{mt} \tag{5}$$

Springel (2020) proposes to think of EV manufacturers as an intermediary connecting EV consumers to charging infrastructure suppliers. Then, equations 2, 4 and 5 define the equilibrium in such two-sided markets. Even though we do not explicitly define the equilibrium using the theory of two-sided markets, we acknowledge that all three equations must be satisfied when both markets are in equilibrium.

3.3 Numerical illustration

In this section, we use a stylized model and numeric simulations to illustrate the indirect network effects and their impact on the effectiveness of different subsidy policies in the EV market. In particular, we will compare the effects of the direct purchase subsidy with the charger subsidy in terms of stimulating EV sales. For this purpose, we abstract all fixed effects away from equation 1 and assume EV adoption to be a log-linear function of the installed base of chargers, purchasing cost and consumer subsidy as follows.

$$\log(q_t) = \theta_C(R_t)\log(N^c_t) + \theta_e \log(p_t - SC^{EV}_t) + \varepsilon_t$$

where q_t is the EV sales at period t and N_t is the stock of chargers at time t. $\theta_C(R_t)$ measures the indirect network effects of chargers on EV adoption and is assumed to be positive reflects. It is assumed to be a function of driving range, reflecting the fact that the indirect network effects could be range-dependent. As a higher driving range implies less reliance on the public charging, i.e. we assume $\theta_C(R)$ to be decreasing in R. p_t is the vehicle price, and S^{EV}_t is the per-unit EV subsidy. ε_t denotes other factors which affect the demand for EVs such as fuel costs.

Furthermore, we simplify the supply of charging infrastructure (equation 5) to the following.

$$\log(N^c_t) = \alpha_N \log(N^{EV}_t) + \alpha_{sc} \log(C_t - SC^c_t) + \eta_t$$

where, C_t denotes the unit fixed cost of building a charger, and SC^c_t is the per charger subsidy provided by the government at period t. Considering vehicle scrappage, we set $N^{EV}_t = \delta N^{EV}_{t-1} + q_t$ as the discounted stock of vehicles in period t, where δ is the survival rate (less than 1). N^{EV}_{t-1} stands for the discounted stock of vehicles at the end of last period. η_t represents other variables that affect the charger supply.

The above equations extends the model setup in Li et al. (2017), allowing the network effects of chargers on EV demand to depend on the battery technology. Because of the log-log specification, $\theta_C(R_t)$ and α_N

represent the elasticities that capture the indirect network effects on the two sides. θ_e measures consumer's price elasticity, while α_{sc} measures the elasticity of entry cost. With a positive shock imposed on either the EV demand side or the charger supply side, the stimulating impacts would be carried forward towards later periods in the market due to the feedback loops.

To illustrate the indirect network effects graphically, we set numeric values for the parameters in the two equations as follows: $\alpha_N = 0.4$, $\varepsilon = 16$, $\eta = 2$, $\delta = 0.9$, $p = 30,000$, $SC^{EV} = 7,500$, $C = 27,000$, $\alpha_{sc} = 0.25$, and assume $\theta_C(R)$ to be specified as follows.

$$\theta_C = \bar{\theta}_C + \xi R$$

where $\bar{\theta}_C$ is the benchmark elasticity (set to be 1.3), R is the battery range, and ξ represents marginal change in elasticity in response to a unit change in range, which is set to be -0.005 (higher range indicates less reliance on chargers).

Because of the indirect network effects, the government can stimulate EV adoption in two ways: subsidizing the EV purchase directly (Policy 1) or subsidizing the charging infrastructure (Policy 2). To compare our findings with the previous studies (*e.g.,* Springel, 2020; Li et al., 2017), we assume a purchase subsidy of \$7,500 per vehicle sale as Policy 1,[14] and a constant per-charger subsidy of SC^c in Policy 2 such that the total budgetary cost of the two policies are equal. We assume the subsidy policies are in effect only for the first 5 periods while other variables such as ε_t and η_t are fixed.

We start with a low battery technology such that the driving range is set at 40 km. The evolution of the EV sales and the cumulative number of chargers due to the two subsidy policies are depicted in Figure 3. We also plot the natural growth paths of the EV sales and the installed base of chargers in a no-subsidy scenario as benchmark in all panels of Figure 3. Because of the indirect network effects, the EV sales and the availability of chargers would keep growing naturally until they reach the steady state, where the inflow of the new vehicles equals the outflow of the scrapped vehicles. As shown in all panels, both Policy 1 and policy 2 can stimulate EV adoption in the first 5 periods and their effects last over periods before they finally vanish, due to the indirect network effects. However, the charger subsidy is more effective in stimulating EV adoption than EV purchase subsidy, which echoes with previous findings in both Springel (2020) and Li et al. (2017).

To compare the effectiveness of the two subsidy policies in different stage of battery technology development, we calculate the ratios of the installed base of EVs in these two subsidy scenarios at the end of the fifth period at different values of driving ranges. As the driving range improves, EVs become less reliant on public chargers, which will then affect the effectiveness of the two policies. Figure 4 plots the ratios of the subsidy effects against different driving ranges. The figure reveals that, when the driving range is relatively low and consumers are more dependent on the chargers, Policy 2 (charger subsidy) is more effective in boosting EV sales than policy 1 (purchase subsidy). Their effectiveness reverses when the driving range increases due to technology improvement. Figure 4 also suggests that price sensitivity affects the relative effectiveness of the two subsidies: when consumers are more sensitive to prices (-1.4), policy 1 becomes more effective in boosting EV sales as consumers are more responsive to price changes.

We then simulate a technology-based EV purchase subsidy, which is the observed policy in the Chinese market, and compare it with the charger subsidy. We extend the EV demand model to incorporate product heterogeneity by assuming that there are two vehicle models with different ranges, which are labelled as H (high range) and L (low range), respectively. They are different in elasticity of EV adoption with respect

[14] This is the same as the purchase subsidy in US.

to the indirect network effects of chargers. The EV demand function is given by,

$$\log(q_{Lt}) = (\bar{\theta}_C + \xi_L)\log(N_t^c) + \theta_e \log(p_{Lt} - SC_L^{EV}{}_t) + \varepsilon_{Lt}$$
$$\log(q_{Ht}) = (\bar{\theta}_C + \xi_H)\log(N_t^c) + \theta_e \log(p_{Ht} - SC_H^{EV}{}_t) + \varepsilon_{Ht}$$

The prices of the two models are set as $p_L = 20,000$ and $p_H = 40,000$. Furthermore, we set $\xi_L = 0$ and $\xi_H = -0.2$. The supply of chargers remains with the same specification while the installed base of EVs now includes both high and low range EVs.

Here we still consider two policy designs: Policy 1 that directly subsidizes the EV purchase with $SC_L^{EV} = 5,000$ and $SC_H^{EV} = 10,000$ for 5 periods, and Policy 2 that subsidizes the chargers with the total spending equivalent to Policy 1 for 5 periods. The high and low ranges are set at , respectively. Figure 5 presents the cumulative EV sales by the end of the subsidy-effective period in the scenarios of these two policies. It shows that Policy 2 leads to more EV sales as consumers rely much on the deployment of chargers at the given battery technology. However, as the chargers have heterogeneous network effects on the EVs with different ranges, these two policies also generate different impact on the sales distribution in EV ranges as shown in Figure 6: Policy 1 results in a larger share of high-range EVs than Policy 2 does for two reasons: 1) purchase subsidy is higher for the high-range vehicles than that for the low-range vehicles; and 2) the high-range EVs are less dependent on chargers and so the subsidized expansion of charger network has lower effects on the high-range EVs.

The simulation results in this section suggest that the relative effectiveness of the subsidy policies greatly hinge on the consumer's price sensitivity and the technology stage in the EV market. Subsidizing EVs or chargers would also result in different distributional impacts on the industry.

3.4 Identification

After taking the logarithm on both sides of equation (2) and then deducting the logarithmic market share of the outside option from that of product j, we end up with the following equation:

$$log(s_{jmt}) - log(s_{omt}) = \tau_j - \theta_e e_{jmt} - \theta_N log(N_{mt}^s) + \theta_C C\{R_j\} \times log(N_{mt}^c) + \theta_g gp_{mt} \times FE_j + \tau_m + \tau_t + \xi_{jmt} \tag{6}$$

Intuitively, the left-hand side of equation 6 measures the market share of product j relative to that of the outside option in market m at time t, which depends on the indirect network effects of charging infrastructure, product quality and factors unique to the particular market and period.

Two identification issues concern the estimation of parameters in equation 6. First, the ownership cost is endogenous since its main component, the vehicle price, is correlated with unobserved product features, which is the error term. To resolve this issue, we adopt three sets of instrumental variables (IVs). The first IV is the EV purchase subsidy. The purchase subsidy is a valid IV for two reasons: 1) it is a component of the expense of EV ownership, but it is set by the government, not by EV manufacturers. Therefore, it is correlated with ownership costs but independent of unobserved product features. 2) The subsidies depend on the vehicle range, which is an observed technical feature independent of unobserved characteristics by assumption. Since range is a key feature that determines EV costs and thereby prices, purchase subsidies are correlated with price through vehicle range but are independent of unobserved features. Second, following Berry and Jia (2010) and Xiao et al. (2017), we use the number of markets in which each product is present as another IV since this variable is pertinent to economies of scale, which is a cost-shifter determining price but is uncorrelated with unobserved characteristics. Third, following Gandhi and Houde (2019) and Miravete et al. (2018), we also construct the third set of IVs using the

observed product features. The IVs in this direction include the sum of the squared distance between product j and all products other than j produced by the same firm producing j ($\mathcal{F}_j$), $Z^{k,1}_{jmt}$ (7a), and the sum of the squared distance between product j and the products of all of the other firms in the same market at the same time, $Z^{k,2}_{jmt}$ (7b), as follows.

$$Z^{k,1}_{jmt} = \sum_{\substack{r \neq j \\ ,r \in \mathcal{F}_j}} (d^k_{rj,mt})^2 \tag{7a}$$

$$Z^{k,2}_{jmt} = \sum_{r \notin \mathcal{F}_j} (d^k_{rj,mt})^2 \tag{7b}$$

where $d^k_{rj,mt}$ is the distance between product j and product r in the dimension of characteristic k in market m at time t. These two groups of instruments in (7) are used to approximate the distribution of products according to product characteristics. Since the characteristic distribution will also determine product substitutability and thus the structures of competition and endogenous prices, this set of IVs can also be used to identify the coefficients of prices.

The second identification issue pertinent to parameter estimation in the demand function is the endogeneity of the number of chargers, N^s_{mt}. Endogeneity issues arise from the interdependence between the EV network and the station network. We use the number of chargers exclusively serving public transportation (including taxis and buses) as the IV for this variable. Since such stations do not serve private EV owners, the number of these chargers is independent of the shocks to EV demand, while it is correlated with the number of public chargers N^s_{mt}, as it captures the same trend in changes in investment costs and local government support for the charging infrastructure. This variable is unique to the Chinese market. Local governments establish these specialized charging infrastructures to guarantee the operation of public transportation.

There is also an endogeneity issue with the parameter identification in equation 5. Due to the interdependence between the networks of EVs and stations, N^{EV}_{mt} is endogenous. Following Li et al. (2017), we use the gasoline price as the IV since it affects the EV population and is simultaneously independent of the stochastic factors included in the error term of equation 5 since gasoline prices are not directly correlated with investment in EV chargers.

4 Data

We apply the monthly data on EV sales and the number of EV chargers of the top 50 prefecture-level cities in EV sales rankings for China for 2016-2019 to our model estimation. The market is defined at the city-month level. Figure 7 shows the geographic distribution of the selected cities. Most of these cities are in coastal regions, while the others are major inland cities. EV sales are summarized using information from the compulsory third party (CTP) insurance of new vehicles. CTP is mandatory for all vehicles on the road in China. Consumers usually buy CTPs when they buy their cars from car dealers, so the number of new vehicles registered with CTPs is very close to the number of vehicles sold. [15] Figure 8 presents

[15] Due to regulations such as vehicle quota systems, consumers may register their cars in cities other than the city of purchase, but they usually purchase the CTP locally, since the insurance company must witness the consumer signing off on the insurance documents. Therefore, the number of CTP purchases is a better proxy for local sales than the vehicle registrations applied in previous research (e.g., Xiao et al., 2017; Li, 2017; Tan et al., 2019). The gap between registrations and insured cars is

the EV sales from our sample and those published by the China Association of Automobile Manufacturers based on their wholesale sales to retailers from 2016 until 2019. Considering that our sample covers only 50 cities in China, the data are representative of the sales population, especially for the last two years of the sample period. We sum up the sales over time and use it as a proxy for the cumulative number of EVs in each city. As the EV population was very low before 2016, this proxy should be close to the cumulative number of EVs.

We further collected EV MSRPs and data on key features, such as range and battery capacity, from Autohome Inc., the leading online platform for car information dissemination in China. We use these key features to define vehicle models, which are distinguished by their distinct combination of weight, power and utility type (SUV, MPV or sedan), in addition to their nameplates. Figure 9 presents the distributions of EVs, including plug-in hybrid EVs (PHEVs) and battery EVs (BEVs), in price and range over the sample period. One salient feature of these distributions is that the number of EVs is rapidly increasing. Additionally, the technical boundary of the driving range has extended to higher levels over time. Most EVs are priced between RMB 100,000 and RMB 300,000. The national average annual wage of Chinese workers is RMB 93,383. The ratio of the average EV price to the average income is approximately two and half times that of developed economies such Norway or the US.[16]

Information on the EV charger network is obtained from the EV Charging Infrastructure Promotion Alliance (EVCIPA). The cumulative numbers of chargers in prefecture-level cities are published by EVCIPA every month. This matches our EV sales data with the same definition of the market. The temporal changes in the cumulative numbers of chargers are attributed to entry and exits, which are unobserved in the data. Information on firm competition is also unobserved. However, given that charging service is relatively homogeneous given the same standards, the quality difference across operators and over time is negligible. Figure 7b shows the penetration of chargers per 1,000 persons in the selected cities of our sample. Apparently, this figure is positively correlated with the penetration of EVs.

Numbers of both AC and DC chargers are reported for both public stations serving all EV drivers and specialized stations serving public transport vehicles only. AC and DC chargers have different charging durations. On average, a vehicle can be fully charged by an AC charger in approximately 8 hours or by a DC charger in 1.5-2 hours. Therefore, the network of DC chargers better solves the range anxiety problem, while the network of AC chargers normally serves neighborhood residents.

Subsidy information is collected from government websites. Purchase subsidies from the central government vary across EV models in different categories of driving range (Table 3). As the central subsidies are at the same level in all cities, we do not observe cross-market variation in central EV subsidies. However, we still observe longitudinal variation in the central subsidies because the government adjusts subsidies every year. Local governments at the provincial and municipal levels have different local subsidy policies, which generate cross-sectional variations in EV ownership costs. Such longitudinal and cross-sectional variation in subsidies helps with the identification of consumers' price sensitivity essentially in the same way as documented by Li (2019). Infrastructure subsidies vary across provinces (or municipalities). More importantly, subsidy practices are quite different across cities. We clean these policies and

especially significant for cities with vehicle quota restrictions, such as Beijing and Shanghai. The actual sales (measured by CTP) are approximately 3 or 4 times the registration quota for Beijing or Shanghai, respectively, implying that quota constraint must be taken into account while estimating vehicle demand using registration data (Li, 2017). The quota effects are subverted while using insurance data since the locally insured cars could be registered to the other places, circumventing the quota restriction.

[16] Springel (2020) documented that the average EV price was NOK 305,075, or USD 37,814 in 2015, while the annual per capita income of Norway was USD 44,041 in that year. Li et al. (2017) documented the average EV retail price net of incentives and annual personal income to be US$ 33,161 and 41,607, respectively.

convert various subsidies into charger-based subsidies using the method elaborated in Appendix A.

The retail prices (RMB per liter) of gasoline with an octane number of 92 are collected from China Petroleum and Chemical Corporation (Sinopec) and PetroChina for all cities in our study over the sample period. We use the average of the prices of these two dominant gasoline suppliers as the instrumental variable for the installed base of EVs in equation 5.

Table 4 reports the summary statistics of variables used for our empirical analysis. On average, the EV subsidies from the central government amount to approximately 10% of the average EV price, while the EV subsidies from the local government are only approximately 6.34% of the central government's subsidies. Therefore, the main variation in subsidies contributing to the identification of price coefficients stems from longitudinal changes in central government subsidies. The average driving range is 174 km, and approximately 50% of the observations have a range of over 150 km, which is higher than that (135 km) of the popular EV models in the US in 2015, as documented in Li et al. (2017).

5 Estimation results and analysis

We apply both ordinary least squares (OLS) and two-stage least squares (TSLS) estimations to the fixed effect models 6 and 5 after demeaning the variables. TSLS estimation is applied to address endogeneity issues. We use White's standard errors for statistical inference, taking into account heteroskedasticity and serial correlation.

5.1 Results of the demand estimation

Table 5 reports the estimation results for the EV demand model (equation 6). Columns (1)-(3) present the results of the OLS regression, while columns (4)-(6) report the results of the TSLS regression, using the IVs elaborated in section 3.4. The difference in the coefficients of the key variables between OLS and TSLS merits discussion. The price coefficients in the OLS regression are overestimated due to the positive correlation between prices and unobserved product features; therefore, the magnitude of the price coefficients in the TSLS estimation is more negative. This difference, although not on a large scale, is still crucial since its impact on welfare analysis could be significant. In contrast, the coefficients of $log(N^c_{mt})$ are underestimated due to endogeneity. As the government downgraded the purchase subsidy but upgraded the subsidy on charging infrastructures, it may have also substituted charging-infrastructure-supporting policies for EV-purchase-supporting policies, both of which are unobserved. This leads to a negative correlation between $log(N^c_{mt})$ and the demand error terms, resulting in an underestimation of the OLS regression. This explains the larger magnitude of the $log(N^c_{mt})$ coefficients in the TSLS results. Considering this bias in OLS estimates, we will use the results from TSLS for further analysis.

Column (4) shows that the indirect network effect of EV chargers is positive and significant at the 10% level. As the dependence on chargers could vary across EV driving ranges, we add the interaction between range (R) and network size into the model and present the results in column (5). The coefficient of the interaction term $R \times log(N^c_{mt})$ is negative and significant at the 5% level, suggesting that EVs' reliance on charging infrastructure decreases with the vehicle driving range. One problem with this model specification is the insignificant coefficient of $log(N^c_{mt})$, which makes the indirect network effect of charging infrastructure on EV adoption suspicious. One possible explanation for this is that reliance on the charger network does not differ by range continuously; alternatively, the marginal reliance could vary over different ranges. Therefore, we further categorize EVs into three segments based on their ranges and the subsidy policy, assuming that the marginal effect of charger networks on their market shares could differ.

The estimation results are reported in column (6). The overall network effect (measured by the coefficient of $log(N^c_{mt})$) is positive and statistically significant at the 5% level. Compared to low-range EVs (with a driving range lower than 150 km), middle- (with a driving range between 150 and 300 km) and high-range EVs (with a driving range higher than 300 km) are less dependent on the charger network, implying that technological progress in batteries may relieve range anxiety and reduce EVs' dependence on charging infrastructures. A counterintuitive finding is that high-range EVs are slightly more dependent on chargers than mid-range EVs. This slight difference could be explained by the fact that high-range EV consumers may have a greater need for long-distance driving than middle-range EV consumers, which renders them more reliant on chargers, especially the fast-charging DC network (as suggested by Table 6). These results also suggest that *if* subsidizing the charging infrastructure is effective in enlarging the charger network, the subsidy on infrastructure investment will promote EV adoption; however, the promotion effect will decrease as the vehicle range increases. Dynamically, this implies that as EV technology progresses and ranges are elevated, if consumers' price sensitivity does not change, subsidies on charging infrastructure will become less effective than EV purchase subsidies in promoting EV adoption. This finding is different from those of Li et al. (2017), who analyze the indirect subsidy effects when the vehicle driving ranges are low[17] and therefore conclude that investing in stations is more effective in boosting EV sales at the early development stage of the EV industry. In summary, the conclusion on policy effectiveness depends on the EV features and battery technology.

To better understand the working mechanism of this indirect network effect, we study the effects of DC and AC networks separately. Replacing $log(N^c_{mt})$ with the cumulative numbers of DC or AC chargers in each market in equation 6,[18] we report the results in Table 6. Overall, the results are similar to those in Table 5 for most of the estimates, with two exceptions. First, all the indirect network effects are positive and at a higher significance level when the number of DC chargers is used to measure the indirect network effects, while they are positive but insignificant when the number of AC chargers is used to measure the indirect network effects. These findings suggest that consumers pay more attention to DC chargers when they make their EV purchase decisions because charging time with DC chargers is much less than that with AC chargers; thus, DC chargers can better alleviate range anxiety. Second, the magnitude of the price coefficients is larger in columns (4)-(6), where the number of AC chargers is applied to measure the indirect network effects. Intuitively, when we underestimate the indirect network effects, more variation in sales is attributed to the variation in price, leading to an overestimation of price sensitivity.

5.2 Results of the charger supply estimation

Table 7 presents the estimation results of the regression on the number of chargers. We present the results of the OLS estimation as a benchmark in columns (1)-(2) and present the results of the TSLS estimation taking into account the endogeneity of EV sales in columns (3)-(4). The main difference in estimation results between these two methods lies in the magnitude of the coefficients of the EV population: OLS underestimates these coefficients relative to with TSLS estimation, suggesting that the error term is negatively correlated with the endogenous EV population. This is reasonable since the government (both central and local) has been replacing (direct) incentives for EV purchases with (indirect) incentives for charging infrastructure for the long-term development of the EV industry. As the indirect incentives increase, the direct incentives decrease, leading to a short-term decline in EV growth. Since any incentives other than subsidies, such as government procurement, are captured by the error term, there is a negative correlation between the error term and the EV population.

[17] The vehicles in their sample fall in the low- and middle-range categories of our sample.

[18] Accordingly, we use their corresponding numbers of specialized chargers as IVs.

The estimates of both EV indirect network effects and subsidy effects on the network of charging infrastructure depend on whether the city fixed effects are controlled or not. The number of chargers is elastic with respect to the EV population (1.108) when city effects are not controlled, while it becomes inelastic (.916) when city effects are controlled. Without controlling for the city effects, we identify the model parameters by deploying both the cross-sectional and longitudinal variation in market shares, EV population and subsidies. As the cross-sectional variation dominates the longitudinal variation, identification mainly comes from the variation across markets. As local governments may also apply quite different incentives other than subsidies to encourage infrastructural investment, which are omitted if city effects are not controlled, we may overestimate the indirect network effect of the EV population and the subsidy effect. This emphasizes the importance of controlling for city fixed effects. The policy implications of such findings are important. When a local government uses the results as a reference to make a decision on the investment in charging infrastructure, it will overestimate the effect of subsidies on or the derived demand of EVs for chargers if they do not factor in the cross-sectional difference in local policies.

Infrastructure subsidies may have lagged effects on the size of the charger network since construction could be time-consuming. Considering such lagged effects, we estimate two specifications for the historical profile of charger subsidies, SC^c_{mt}, in equation 5 : 1) the subsidies at time t only and 2) the subsidies at time t and $t-1$, which take into account the lagged effects of subsidies on charging infrastructure investment. We progressively add the one-month-lagged subsidy and the two-month-lagged average subsidy of a city into the model. The estimation results with lagged subsidies are presented in Table A-3. Most of the estimation results are insensitive to the lagged effects of subsidies. When we gradually add lagged subsidies of different periods into the model, the estimates of EV indirect network effects will not change significantly. Actually, the lagged subsidy variable spreads the total effects of the subsidies on the number of chargers. This is because subsidy policies usually remain unchanged and last for a while once they are granted; therefore, the lagged subsidies will be the same as the current subsidies, so they simply spread the total effect of the current subsidies.

Given the above discussion of the findings, we will use column (6) in Table 7 for further analysis. The indirect network effect of the EV population on charger numbers is higher than that of the US market estimated by Li et al. (2017): our results suggest that when the EV population increases by 1%, the number of chargers will increase by 0.916%, while Li et al. (2017)'s corresponding estimate is 0.613% with their preferred model specification. This difference could be explained by the different entry and operation costs of charging infrastructure between the US and China. The production and installation costs of a single port charging unit range from \$10,000 to \$40,000 for DC fast charging in the US,[19], while they are only approximately \$ 19,000 in China (see section 2 for details). The total operating costs are even lower in China, given that the country has much lower labor costs.

Subsidies can stimulate investment in charging infrastructure. When the subsidy increases by 1%, the charger number increases by 0.082%. This result is different from previous findings by Li et al. (2017), who suggest that the charging station tax credit has no significant effects on charger supply; however, our finding is close to the estimates by Springel (2020), who find that an increase in charging equipment subsidy by NOK 10,000 (or an 188% increase relative to the mean of equipment subsidy), the number of chargers increases by 18.32%, amounting to an elasticity of 0.098%.

[19]Costs Associated with Non-Residential Electric Vehicle Supply Equipment, US Department of Energy, November 2015.

6 Counterfactual analysis

6.1 Methodology

We simulate scenarios of changes in subsidies to compare their effects on EV adoption and their impact on consumer surplus. Our counterfactual analysis proceeds with the following assumptions:

Assumption 1 *The individual manufacturer's vehicle supply is perfectly elastic such that EV prices do not change as a result of subsidies.*

Chinese manufacturers set the MSRPs for EVs, which usually do not vary over time. As introduced in section 2, the Chinese EV industry is very competitive, which supports assumption 1.

Assumption 2 *EV consumers have the same driving patterns as ICEV consumers.*

Our estimates of externality depend on vehicle usage. As such information is unavailable in our dataset, we intend to adopt it from previous literature. However, to the best of our knowledge, previous research on the Chinese EV market has not documented drivers' usage patterns. However, the driving patterns of Chinese ICEV consumers are available in the literature (Xiao et al., 2017). Therefore, Assumption 2 is crucial for the externality estimation. [20]

Assumption 3 *Consumers' ecological preferences are independent of the power generation process. The electricity price is rigid and independent of power generation methods.*

This assumption is important for the prediction of demand in different power generation scenarios, which will ultimately determine the externalities of vehicle usage. Choi et al. (2018) found survey evidence that consumers' preference for EVs may depend on the type of electricity generation in the region.Their analysis results show that changing the electricity generation mix to a renewable-oriented mix can increase BEVs' market share by up to 10%. Additionally, since the electricity costs change in the electricity generation mix, we expect that the electricity price will also change when a more eco-friendly power generation method is adopted, which will further increase the adoption of EVs. Our simulation abstracts away from such changes for two reasons: 1) consumers' ecological preference, if any, is captured by various fixed effects but is not identifiable; and 2) the price rigidity assumption is common among necessities such as electricity.

We use compensating variation (CV) to measure changes in consumer surplus due to some exogenous policy changes. Theoretically, CV refers to the extra payment transfer that a customer needs in a scenario to obtain his or her initial utility in a benchmark scenario, and thus, it is approximately equal to the negative changes in consumer surplus. Following Nevo (2000), we compute the CV for an individual in scenario c, CV^c, relative to a benchmark scenario o as follows:

$$CV^c = \frac{ln[\sum_{k=0}^{J} exp(\delta_k(e_k^o, N^{s,o}))] - ln[\sum_{k=0}^{J} exp(\delta_k(e_k^c, N^{s,c}))]}{\theta_e(\overline{1/e})} \tag{8}$$

where e^s and e^o are the equilibrium ownership cost in scenario c and benchmark o, respectively, and $\overline{1/e}$ is the average of the inverse prices over all products in the market. Intuitively, for a logit model, the expected utility from purchases (including the outside option) is the logarithmic sum of the exponential components of the indirect utility function other than idiosyncratic tastes (the error term); therefore, the numerator in equation 8 indicates the difference in expected utility between any scenario of interest and the benchmark

[20] Davis (2019) finds that EVs are driven considerably fewer miles per year on average than gasoline-powered vehicles in the US market. If this behavioral pattern also applies to Chinese consumers, our externalities will be overestimated.

scenario. To convert this value to a pecuniary value, we divide the difference by the derivative of the utility with respect to price, which is the marginal pecuniary value of the utility.

Changes in vehicle purchase subsidies or infrastructure subsidies result in changes in ownership costs e or the number of chargers N^c, leading to consumer surplus variation. The total change in consumer surplus is then approximated by $\Delta CS = M \times \overline{CV^s}$, where M is the market size. To obtain the CV for each scenario, we simulate a case of no subsidies and use it as a benchmark.

Another important measure in our welfare analysis is the externality from pollution emissions since the main purposes of both EV purchase subsidies and infrastructure subsidies are to reduce emissions from traditional ICEVs. Such externalities depend on vehicle usage and thus on assumptions of vehicle travel distance, marginal externality, and vehicle lifetime. Following Assumption 2, we adopt the annual travel distance of ICEVs in the literature (*e.g.,* Xiao et al., 2017) on the Chinese auto industry: 17,988 km. The lifetime of EVs is different from that of ICEVs in that it depends mainly on the lifetime of the battery. Usually, EVs will be scrapped when it is time to replace the battery since the replacement cost is very similar to a vehicle's price. Therefore, we adopt the normal lifetime of EV batteries, which is currently 7 years, as the EV lifetime. The pollution externality of EV consumption mainly comes from emissions from power generation, which depends on the methods of power generation. We discuss the assumption of marginal externalities with different power generations in Appendix B. Then, the externalities of vehicle j are given by

$$EC_j = T \times VMT \times BC_j/R_j \times MEC \tag{9}$$

where T is the lifetime in years, VMT is the annual vehicle miles traveled, and BC_j is the battery capacity of vehicle j, which is the product of battery energy density and volume. This variable measures the electricity storage capacity of the battery. R_j is the driving range; then, the ratio of BC_j/R_j is the electricity consumption per unit of driving distance. MEC is the marginal externality costs. The case of no subsidies is also used as a benchmark to calculate the externality changes.

6.2 Experiments with EV subsidies

We first examine the effects of EV purchase subsidies by simulating counterfactual EV purchase subsidy changes and comparing the corresponding equilibrium to that observed (null scenario). We use the data for the period from June to December 2018 for this analysis. We simulate a scenario in which the subsidy scheme remains the same as that of 2017 (scenario i). As shown in Table 3, this case actually simulates the scenario in which the downgrades of subsidies on low-range EVs and upgrades of subsidies on high-range EVs, especially those with a range above 300 km (a newly introduced category in the subsidy scheme of 2018), had never happened. To decompose the effects of the subsidy changes in these two directions, we simulate an intermediate subsidy scheme (scenario ii), which only reduces the subsidy of existing categories in the subsidy scheme of 2017 to the level of 2018 without creating new subsidy categories.[21] Table 8 summarizes the subsidies in various scenarios. Comparing scenarios (i) with (ii), we can learn the equilibrium and welfare effects of downgrading subsidies on low-range cars, and comparing scenarios (ii) with the null scenario, we can learn the equilibrium and welfare effects of upgrades of subsidies on high-range cars. The comparative statics between the null and (i) scenarios demonstrate the composite effects of both subsidy upgrades for high-range EVs and subsidy downgrades for low-range EVs. The estimation results are presented in Table 9.

[21] In this case, the subsidy for vehicles with ranges above 250 km is RMB 34,000.

6.2.1 Direct effect on EVs

Our results show that the half-year EV sales in scenario (i) have decreased by RMB 38,878 (or approximately 6.5% of the sales of the null scenario) due to subsidy changes. However, without the new subsidy categories on the high-range end, sales in scenario (ii) could have further decreased by an additional RMB 31,887. Therefore, the upgraded subsidies on vehicles in the newly created category have partially offset the downgraded subsidies on low-range vehicles and moderated the decline in sales. More importantly, this scheme modification has also changed the sales distribution, shifting sales to the high-range end. Figure 10 presents the changes in sales by EV range in two simulated scenarios relative to observed sales (null scenario). Figure 10a shows that if the subsidy scheme of 2017 continued to 2018, the sales of low-range vehicles (with a range less than 300 km) should have been higher, while the sales of high-range vehicles (with a range more than 300 km) should have been lower. Figure 10b demonstrates the effects of upgrades of subsidies on high-range vehicles (with a range of more than 300 km). On average, the upgraded subsidies on the newly created categories have increased sales by approximately 10%. Apparently, the new subsidy scheme favors the diffusion of high-range EVs.

Subsidy scheme changes reduce consumer surplus by RMB 3.906 billion (comparing the null and (i) scenarios). However, without upgrades to the new subsidy category, this loss could have been RMB 7.104 billion (comparing scenarios (i) and (ii)). Therefore, subsidy upgrades for the high-range category partially offset the welfare loss. In terms of per capita consumer surplus, this redesign of the subsidy scheme actually offsets 45% of the potential loss on the consumer side. The total changes in consumer surplus are asymmetrically distributed over buyers of EVs in different range categories. Table 10 shows that low-range EV consumers are worse off from the subsidy scheme changes (or equivalently, the simulated scenario (i) will generate higher surplus for low-range EV consumers compared with the null scenario), while high-range EV consumers are better off. On average, the EV buyer surplus decreases by RMB 4,969 per capita. The upgrades of subsidies on high-range EVs make their buyers significantly better off: buyers of EVs with ranges between 300 and 400 km obtain an extra surplus of RMB 11,933, while those of EVs with ranges above 400 km obtain an extra surplus of RMB 13,521. The consumer surplus gain from upgrading subsidies on high-range EVs (comparing the null and (ii) scenarios) is much higher than that from a subsidy scheme change (comparing the (i) and null scenarios) since the subsidies for high-range EVs are assumed to be capped at RMB 34,000 in scenario (ii), following the 2018 scheme, while they are assumed to be capped at RMB 44,000 in scenario (i), following the 2017 scheme.

As EVs also generate externalities arising from power generation or charging processes, we also investigate the changes in externalities in response to changes in subsidies. Overall, compared to the subsidy scheme of 2017, the new subsidy scheme of 2018 could have reduced externalities by RMB 650 million at a marginal external cost of RMB 1.155/kWh or by RMB 139 million at a marginal external cost of RMB 0.246/kWh over 7 years, with the assumption of the annual driving distance discussed above. Were it not for the upgrades of subsidies on the high-range EVs, the externalities would have further decreased by RMB 634 million or 135 million, depending on the assumptions of marginal external costs. Additionally, our discussion on externalities assumes the externalities from the outside option to be zero. Given that purchasing ICEVs is one of outside options, it is also possible that the marginal external costs of outside options could be even higher than those of EVs. If this is the case, the more EVs are consumed, the more externalities are reduced. Then, the conclusion on the externalities will reverse. Comparing the marginal externalities per 100 km of EVs to those of ICEVs as documented by (Parry et al., 2007), however, we find that EVs generate more externalities than ICEVs with the current power generation method. Therefore, our main conclusion should remain unchanged even in light of externalities from outside options.

Government expenditures would have been RMB 3.758 billion higher if the government continued its

subsidy scheme from 2017 to 2018. The downgrades in subsidies on low-range EVs reduced government expenditures by RMB 8.125 billion, but the upgrades in subsidies on high-range EVs increased government expenditures by RMB 4.366 billion.

The overall effects of the EV subsidy changes depend on the assumption of marginal externality, which further depends on the methods of power generation. When the marginal externality is at a high level, the subsidy scheme change from its structure of 2017 to that of 2018 leads to a welfare gain due to the saved government expenditure and reduced externalities exceeding the decreased consumer surplus. However, when the marginal externality is at a low level, the reduced costs are not enough to offset the reduction in consumer welfare. Therefore, EV subsidies could be more easily justified in a nation with more electricity generated through clean energy, such as Norway (Springel, 2020).

6.2.2 Indirect network effects on the charger supply

Our analysis thus far has assessed the direct effect of subsidies on EV demand without considering the mutual indirect network effects between EVs and chargers. These indirect network effects could accentuate the subsidy effects through the interdependence between sales and charger numbers. Moreover, the upgrades of subsidies on high-range EVs could spill over to low-range EVs through the indirect network effects between EVs and chargers, which may change the simulated EV sales distribution using the demand function (equation 2) only. This section investigates the indirect network effects of subsidies. We repeat the simulation in the last section but solve for equilibrium EV sales and charger numbers simultaneously using equations 2 and 5. The results corresponding to scenarios (i) and (ii) are reported as scenarios (iii) and (iv), respectively, in Table 9.

The indirect network effects marginally accentuate the subsidy effects on EV sales (less than 1%). In particular, had the subsidies for most range categories not been downgraded, the EV sales would have remained at a higher level considering the indirect network effects (scenario (iii)) than that without considering such effects (scenario (i)). Additionally, indirect network effects make the effects of upgraded subsidies on EV sales more notable (comparing the difference between the null and (i) scenarios and the difference between the null and (iv) scenarios).

Figure 11 presents the changes in EV sales by range, considering the indirect network effects. No significant difference from Figure 10 is observed in this diagram. The only visible difference lies in the sales changes in the low-range categories: the subsidy effects on high-range EVs are first passed to the number of chargers and further passed through the indirect network effects of chargers on EV sales to low-range EVs, so the sales changes for some low-range EVs are larger compared with the results without considering the indirect network effects. However, the difference is very marginal, implying that the spillover effect of EV subsidies across different range categories through indirect network effects is weak.

6.3 Experiments with infrastructure subsidies

We also simulate the scenario in which EV subsidies are replaced by infrastructure subsidies. To make the results comparable to those for the scenarios of EV subsidy changes, we constrain the total amount of infrastructure subsidies to the level of EV subsidies in the null scenario in the previous section. Intuitively, this scenario simulates the case in which the government substitutes infrastructure subsidies for EV subsidies. Subject to this constraint, we solve equations 6 and 5 simultaneously for equilibrium EV sales and the number of chargers. Then, we calculate the CV and externalities using equations 8 and 9, respectively. The results are reported in the column corresponding to scenario (v) in Table 9.

With equal-size subsidy expenditures, EV subsidies are 34.4% more effective than charger subsidies in promoting EV sales. Our findings for sales changes are significantly different from those of Li et al. (2017), who suggested that infrastructure subsidies are more effective than EV subsidies in promoting EV adoption. Comparing our results from the EV demand estimation with those in Li et al. (2017), we find that Chinese consumers are more sensitive to prices but less sensitive to the size of charger networks than consumers in the US. Price sensitivity depends on income. On average, Chinese consumers have lower income than American consumers, which explains their higher price sensitivity. Consumers' sensitivity to the indirect networks of chargers depends on EV features, especially driving range. The sample period of Li et al. (2017) is 2011-2013, during which "the range is sufficient for daily household vehicle trips but may not be enough for longer distance travels" (Li et al., 2017, page 95). Consequently, they found that the charger network can more effectively reduce range anxiety. In our sample, however, the average EV driving range is 174.5 km (Table 4). The technological advance in EV driving distance significantly reduces consumers' range anxiety and makes EV drivers less dependent on the charger network. Moreover, China has the largest charger network globally. When the network reaches some scale, the marginal utility of network expansion diminishes. Consequently, as governments replace EV subsidies with infrastructure subsidies, vehicle demand drops.

The policy implications of such findings are very important: the effectiveness of alternative policies depends on consumers' price sensitivity, the stage of EV technology progress and the scale of the charger network. Charging infrastructure is crucial in the early stages of the EV industry since range anxiety is a serious concern among consumers, especially when the driving range is low and the charging infrastructure is sparse. Additionally, as EV quality (especially in terms of driving range) is low, EV subsidies are not effective in significantly increasing demand. In this stage, therefore, the government could substitute EV subsidies with infrastructure subsidies. This replacement becomes more effective in promoting EV adoption when consumers' price sensitivity is lower. However, as the circumstances of the Chinese markets are quite different from these, the government's optimal subsidy choice should change accordingly.

This subsidy replacement also changes the composition of sales to the low-range end. Figure 12 presents the percentage changes in EV sales in scenario (v) relative to the null scenario against the EV range groups. On average, EV sales for all groups, except the lowest-range group, fall when EV subsidies are replaced with charger subsidies. The decline in sales is lower for low-range groups than for high-range groups. This change in sales composition is quite different from that in Figure 10b in the sense that EV subsidies can more effectively target the EV categories the government would like to promote, while charger subsidies favor EVs in the low-range categories more. Therefore, our findings suggest that a well-designed policy instrument also contributes to EV technology upgrading.

The externality in scenario (v) is lower mainly because sales drop by a large magnitude. Moreover, we calculate the externality per vehicle when EV subsidies are replaced with charger subsidies using $(\Delta EC^{v} - \Delta EC^{null})/(sales^{v} - sales^{null})$, where the subscript of each variable indicates the scenarios. The per vehicle externality is close to that caused by the upgrades of subsidies on high-range vehicles but is approximately 16% higher than that caused by the downgrades of subsidies on low-range vehicles. This implies that high-range vehicles could generate more externalities than low-range vehicles. The reason for this is that the main technology used to expand the range is to increase battery cells (and therefore battery weights) rather than to increase battery efficiency. Consequently, high-range vehicles have a lower fuel economy. Therefore, our findings suggest that infrastructure subsidies, in contrast to well-designed EV subsidies in favor of high-quality EVs, are a more effective abatement policy, at least under the current circumstances of power generation and battery technology.

Overall, replacing EV subsidies with charger subsidies leads to welfare loss since the loss in consumer

surplus dominates the reduction in externalities. Moreover, considering that the fuel economy of high-range cars may improve as battery technology develops and power generation is transferred to clean-energy methods, the externality reduction from this replacement will be much lower. This finding suggests that EV subsidies are a more efficient policy than charger subsidies in promoting EV adoption.

7 Conclusions

High ownership costs and range anxiety have been obstacles to the development of the EV industry. China has been stimulating the development of the EV industry by subsidizing EV consumers for a decade. Recently, however, consumer subsidies that have fueled domestic EV sales have already been reduced significantly and were scheduled to be fully phased out in 2020. Alternatively, charger subsidies have been widely adopted. Previous studies (Li et al., 2017; Springel, 2020; Meunier and Ponssard, 2020) on the indirect network effects of charging infrastructure on EV adoption suggest that charger subsidies could be more efficient than EV subsidies in promoting EV sales. However, their conclusions are confined to the conditions of the EV base, installed stations, and EV technology. Any intention to extend the empirical conclusions to another market in different conditions could be misleading, especially considering the dynamic features of the industry.

This paper investigates the mutual indirect network effects between EV adoption and charger infrastructure, applying updated data on EV sales and charger numbers in China. We assess the effectiveness of two types of subsidies, EV purchase subsidies and charging infrastructure subsidies, in promoting EV sales and their impact on welfare, considering their indirect network effects on each other. Different from previous findings (*e.g.,* Li et al., 2017; Springel, 2020), our empirical results suggest that EV subsidies are more effective in promoting sales and more efficient in the sense that the welfare loss from EV subsidies is lower than that from charger subsidies. Moreover, by examining the impact of subsidies on EV sales distribution and welfare distribution over vehicle ranges, we find asymmetric impacts of subsides on vehicles of different ranges. Updated EV subsidies favor high-range vehicles, while charger subsidies favor low-range vehicles. Hence, the policy implications of these two types of subsidies are quite different, particularly in terms of their contribution to the technology diffusion of the industry.

Another salient dynamic feature of the Chinese economy is the development of new energy. Power generation is shifting from mainly coal-firing methods to clean-energy methods, such as solar and nuclear methods. This transfer is important for our policy analysis since it could change the assessment of the externalities of EV usage. Our empirical results suggest that policy efficiency depends on our assumption of marginal externalities. An important extension to this paper, therefore, could be the estimation of marginal externalities of EVs in the current situation of the Chinese market.

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Table 1a: Leading firms and concentration index in the Chinese EV and ICEV markets (2019)

Rank	EV		ICEV	
	Manufacturer	Share	Manufacturer	Share
1	BYD auto Co., Ltd.	21.91%	FAW-Volkswagen Automotive Co., Ltd	10.95%
2	Zhejiang Geely Automobile Co.,Ltd	8.10%	SAIC Volkswagen Automotive Co., Ltd	10.56%
3	Beijing Electric Vehicle Co., Ltd	8.06%	SAIC General Motors Corporation Limited	8.38%
4	Saic Motor Corporation Limited	6.08%	Zhejiang Geely Automobile Co.,Ltd	6.72%
5	Chery Automobile Co., Ltd	4.74%	Dongfeng Nissan Passenger Vehicle Company	6.08%
6	Saic GM Wuling Automobile Co., Ltd	4.68%	GAC Honda Automobile Co., Ltd.	4.56%
7	Great Wall Motor Company Limited	4.62%	DongfengÊHondaÊAutomobile Co., Ltd	4.07%
8	Chongqing Changan Automobile Co., Ltd	4.18%	GAC Toyota Motor Co., Ltd	3.80%
9	GAC Motor Co., Ltd	3.96%	Great Wall Motor Company Limited	3.34%
10	Anhui Jianghuai Automobile Group Corp.,Ltd	3.89%	Chongqing Changan Automobile Co., Ltd	3.32%
CR4[a]	44.14%		36.62%	
CR10[b]	70.21%		61.78%	
HHI[c]	0.0823		0.0533	

[a] Concentration ratio of the top 4 firms, $\sum_{i=1}^{4} s_i$, where s_i is the market share of firm i.
[b] Concentration ratio of the top 10 firms, $\sum_{i=1}^{10} s_i$, where s_i is the market share of firm i.
[c] Herfindahl-Hirschman index, $\sum_{i=1} s_i^2$.

Table 1b: Concentration index of the Chiese EV and ICEV industries over years 2016-2019

Year	EV			ICEV		
	CR4[a]	CR10[b]	HHI[c]	CR4	CR10	HHI
2016	67.76%	95.75%	0.1608	33.22%	57.57%	0.0464
2017	62.10%	91.50%	0.1226	31.16%	56.65%	0.0439
2018	58.12%	83.40%	0.1101	34.44%	58.54%	0.0482
2019	44.14%	70.21%	0.0823	36.62%	61.78%	0.0533

[a] Concentration ratio of the top 4 firms, $\sum_{i=1}^{4} s_i$, where s_i is the market share of firm i.
[b] Concentration ratio of the top 10 firms, $\sum_{i=1}^{10} s_i$, where s_i is the market share of firm i.
[c] Herfindahl-Hirschman index, $\sum_{i=1} s_i^2$.

Table 2: Major charging station firms in China

Order #	Corporate Name	Establishment Time	City of Headquarter	Number of Charging Stations[a]
1	Qingdao Teld New Energy	9/4/14	Qingdao, Shandong	144,000[b]
2	Star Charge	9/16/14	Changzhou, Jiangsu	112,000
3	State Grid Corporation of China	5/13/03	Beijing	88,000
4	Jiangsu YKC New Energy Technology	11/1/16	Nanjing, Jiangsu	33,000
5	EV Power	11/6/14	Shanghai	25,000
6	AnYo Charging	10/13/15	Shanghai	18,000
7	Potevio New Energy	10/29/10	Beijing	14,000
8	Shenzhen Car Energy Network	4/5/16	Shenzhen, Guangdong	12,000

[a] Data source: The China Electric Vehicle Charging Infrastructure Promotion Association. The eight operators together represented 90.0 % of all stations in operation across the country.
[b] The statistics are up to November 2019.

Table 3: Subsidy on BEVs from the central government of China

Time		Range (km)		Subsidy	Number of	Total EVs	Percentage of
Year	Month	lb[a]	ub[b]	(RMB 10,000)	eligible EVs		eligible EVs
2009	1			6			
2010	6			0.3/kWh			
2013	1	80	150	3.5			
		150	250	5			
		250		6			
2014	1	80	150	3.325			
		150	250	4.75			
		250		5.7			
2015	1	80	150	3.15			
		150	250	4.5			
		250		5.4			
2016	1	100	150	2.5	1	39	2.56%
		150	250	4.5	30		76.92%
		250		5.5	8		20.51%
2017	1	100	150	2	0	82	0.00%
		150	250	3.6	50		60.98%
		250		4.4	32		39.02%
2018	2-6	100	150	1.4	1	76	1.32%
		150	250	2.52	36		47.37%
		250		3.08	39		51.32%
	6	150	200	1.5	8	123	6.50%
		200	250	2.4	13		10.57%
		250	300	3.4	22		17.89%
		300	400	4.5	54		43.90%
		400		5	26		21.14%
2019[c]	3-6	150	200	0.9	1	108	0.93%
		200	250	1.44	1		0.93%
		250	300	2.04	5		4.63%
		300	400	2.7	56		51.85%
		400		3	45		41.67%
	6	300	400	1.8	45	135	33.33%
		400		2.5	77		57.04%

[a] Lower bound of vehicle range applicable to the corresponding subsidy.
[b] Upper bound of vehicle range applicable to the corresponding subsidy.
[c] The phase-in period of the 2019 policy is from March 26 to June 25. During this period, vehicles complying with the technical standards of year 2018 but not the technical standards of year 2019 were subject to 10% of the 2018 subsidy; vehicles complying with the technical standards of year 2019 were subject to 60% of the 2018 subsidy.

Table 4: Data summary

	Number of Obs	Mean	Standard deviation	Min	Max
EV demand variables					
Sales	86785	26.812	131.478	1	11038
Price (MSRP, RMB 10,000)	86785	20.662	9.96	4.58	108.8
EV subsidies central (RMB 10,000)	86785	2.129	1.816	0	6.6
EV subsidies local (RMB 10,000)	86785	0.135	0.825	0	15.74
Range[a](km)	86785	174.465	156.216	0	550
Dummy of range categories (km)					
$[150, 300)$	86785	0.179	0.384	0	1
$[300, \text{inf})$	86785	0.335	0.472	0	1
Gasoline price (RMB/Liter)	86785	6.508	0.463	4.785	7.723
Fuel Economy (kWh/100 km)	86785	11.768	7.717	0	98
Charger supply variables					
Number of Chargers	2352	2338.737	4668.265	4	36883
AC	2352	1785.683	3897.316	4	31973
DC	2352	533.054	924.534	0	6199
Cumulative number of EVs	2352	17667.7	34868.01	7	265816
Charger subsidies (RMB 10,000)	2352	7.016	11.524	0	103.809

[a] Theoretical driving range published by the Ministry of Industry and Information Technology, China. In some hybrid models, a battery provides electricity to start the car before the fuel-powered engine is engaged and also powers vehicle accessories. The theoretical range of such vehicles is zero.

Table 5: Results of the demand estimation

	OLS			TSLS		
	(1)	(2)	(3)	(4)	(5)	(6)
log(price - subsidy)	-1.881***	-1.878***	-1.947***	-1.914***	-1.972***	-1.985***
	(0.361) [a]	(0.362)	(0.366)	(0.394)	(0.396)	(0.396)
$log(N^c_{mt})$[b]	0.049*	0.053*	0.130***	0.132*	0.095	0.170**
	(0.027)	(0.027)	(0.028)	(0.073)	(0.072)	(0.075)
gasoline price	0.002	0.003	0.005**	0.002	0.003	0.004**
$\times$ fuel economy [c]	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$R \times log(N^c_{mt})$[d]		-0.017***			-0.015***	
		(0.005)			(0.006)	
$C\{150km \leq R < 300km\} \times log(N^c_{mt})$ [e]			-0.167***			-0.111***
			(0.019)			(0.023)
$C\{300km \leq R\} \times log(N^c_{mt})$			-0.062***			-0.055***
			(0.016)			(0.020)
Number of Observations	86656	86656	86656	86656	86656	86656
Period FE	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y
EV model FE	Y	Y	Y	Y	Y	Y
R^2[f]	0.41	0.41	0.41			
Adjust R^2	0.40	0.40	0.41			
First-Stage F-statistics						
Price				857.77	731.38	624.95
Station				103.82	118.94	140.20
First-Stage R^2						
Price				0.92	0.92	0.92
Station				0.15	0.16	0.17

[a] White's standard errors in parentheses; * p<0.05, ** p<0.01, and *** p<0.001.

[b] N^c_{mt} is the number of chargers in market m at time t.

[c] The gasoline price is measured in RMB/liter. The fuel economy of electric vehicles measures the consumption of electricity (kWh) for a driving distance of 100 km, so it is measured in $kWh/100km$. The data are published by the Ministry of Industry and Information Technology of China.

[d] R is a continuous variable measuring the EV driving range.

[e] $C\{150km \leq R < 300km\}$ is a binary variable equal to 1 if the driving range of an EV falls in the interval of $[150km, 300km)$ and 0 otherwise. Other range categorical variables are defined in a similar way. The benchmark of these categorical variables is the category of vehicles with driving ranges less than 150 km.

[f] Only the R^2 of the OLS estimation is reported since the R^2 of the TSLS estimation does not have statistical significance.

Table 6: Results of the demand estimation with different measures of indirect network effects

	DC network effects			AC network effects		
	(1)	(2)	(3)	(4)	(5)	(6)
log(price - subsidy)	-1.989***	-1.930***	-1.976***	-2.009***	-2.054***	-2.074***
	(0.395)[a]	(0.393)	(0.398)	(0.395)	(0.398)	(0.396)
$log(N^c_{mt})$[b]	0.155***	0.151***	0.157***	0.074	0.047	0.149*
	(0.054)	(0.053)	(0.054)	(0.083)	(0.082)	(0.085)
gasoline price	0.003	0.004*	0.006***	0.003	0.003	0.005**
$\times$ fuel economy [c]	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$R \times log(N^c_{mt})$[d]		-0.016***			-0.016***	
		(0.005)			(0.006)	
$C\{150km \leq R < 300km\} \times log(N^c_{mt})$ [e]			-0.122***			-0.126***
			(0.021)			(0.023)
$C\{300km \leq R\} \times log(N^c_{mt})$			-0.057***			-0.058***
			(0.019)			(0.020)
Period FE	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y
EV model FE	Y	Y	Y	Y	Y	Y
First-stage F-statistics						
Price	854.04	731.21	624.63	860.54	738.40	645.59
Station	85.88	72.72	70.97	71.80	90.40	116.98
First-Stage R^2						
Price	0.92	0.92	0.92	0.92	0.92	0.92
Station	0.92	0.92	0.92	0.91	0.91	0.91
J-test	201.66	202.71	287.47	203.41	208.55	291.51

[a] TSLS is applied to the demand estimation. White's standard errors in parentheses; * p<0.05, ** p<0.01, and *** p<0.001.

[b] N^c_{mt} is the number of DC chargers in columns (1)-(3) and the number of AC chargers in columns (4)-(6).

[c] The gasoline price is measured in RMB/liter. The fuel economy of electric vehicles measures the consumption of electricity (kWh) for a driving distance of 100 km, so it is measured in $kWh/100km$. The data are published by the Ministry of Industry and Information Technology of China.

[d] R is a continuous variable measuring the EV driving range.

[e] $C\{150km \leq R < 300km\}$ is a binary variable equal to 1 if the driving range of an EV falls in the interval of $[150km, 300km)$ and 0 otherwise. Other range categorical variables are defined in a similar way. The benchmark of these categorical variables is the category of vehicles with driving ranges less than 150 km.

Table 7: Results of the estimation of the charger supply function

	OLS		TSLS	
	(1)	(2)	(3)	(4)
$log(N_{mt}^{EV})$	0.933***	0.330***	1.108***	0.916***
	(0.076)[a]	(0.100)	(0.113)	(0.268)
log(subsidy) ($log(SC_{mt}^{c})$)	0.304***	0.073**	0.275***	0.082**
	(0.087)	(0.031)	(0.091)	(0.033)
Number of observations	2352	2352	2352	2352
Period FE	Yes	Yes	Yes	Yes
City FE	No	Yes	No	Yes
First-Stage F-statistics			335.19	93.36

[a] Standard errors in parentheses. * p<0.10, ** p<0.05, and *** p<0.01

Table 8: Summary of the subsidies in the counterfactual scenarios

Range categories		Subsidies (RMB 10,000)		
			Scenarios	
LB[a](km)	UB[b](km)	Null	(i)	(ii)
150	200	1.5	2	1.5
200	250	2.4	3.6	2.4
250	300	3.4	4.4	3.4
300	400	4.5	4.4	3.4
400	max	5	4.4	3.4

[a] Lower bound of the range category.
[b] Upper bound of the range category.

Table 9: Equilibrium and welfare effects of EV subsidy changes

Counterfactual Scenarios of		EV subsidies				Charger subsidies
Indirect network effects		No	No	Yes	Yes	Yes
Scenario Index	Null	(i)	(ii)	(iii)	(iv)	(v)
Sales[a]	599471	638349	567584	639616	566787	445889
Subsidies (million RMB)	23123	26882	18757	26937	18732	23123
Changes in consumer surplus (ΔCS, million RMB)[b]	21576	25483	18379	26063	18745	5267
Changes in consumer surplus per capita (ΔCS, RMB)	14	17	12	17	13	4
Changes in externalities (ΔEC, million RMB)[c]	3612	4262	2977	4340	3024	621
Changes in externalities (ΔEC, million RMB)[d]	886	1025	751	1049	766	189

[a] Half-year sales for selected cities.
[b] The benchmark is consumer surplus in the scenario without EV subsidies.
[c] The benchmark is the externalities in the scenario without EV subsidies. The marginal externality of EV is assumed to be RMB 1.155/kWh.
[d] The marginal externality of EV is assumed to be RMB 0.246/kWh.

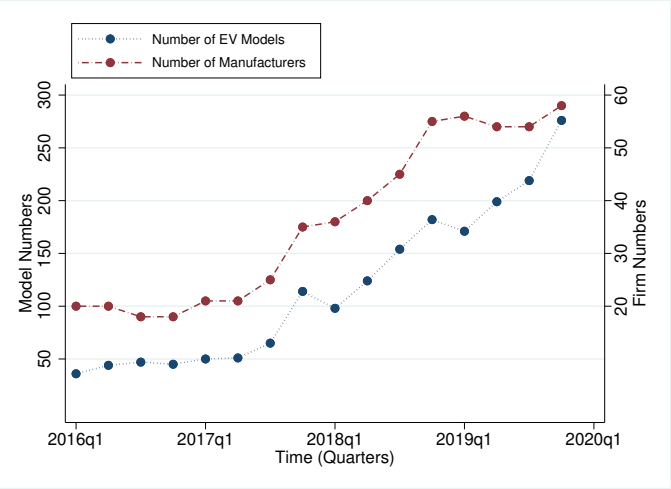
Table 10: Changes in consumer surplus by EV ranges in the counterfactual scenarios

Range (km)	Difference in per capita CS (RMB, (i)-null)[a]	Difference in per capita CS (RMB, (ii)-null)[b]
100∼150	6113	0
150∼200	13609	0
200∼250	8830	0
250∼300	7729	0
300∼400	-1085	-11933
>400	-4951	-13521
phev	0	0
All EVs	4969	-5157

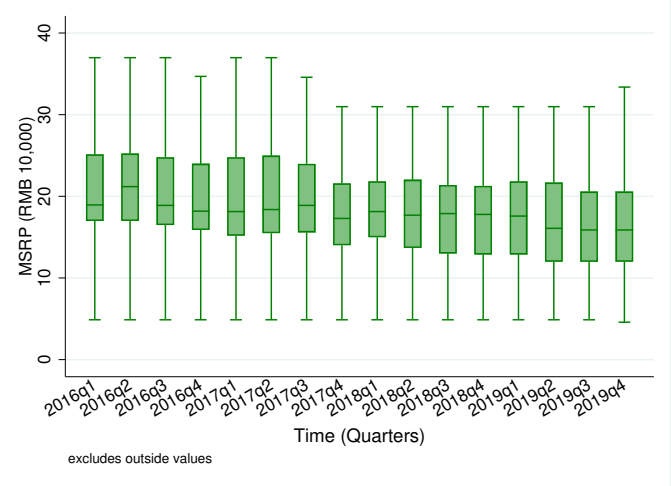
[a] The per capita CS is calculated using the compensation variation that makes representative consumers in each category of ranges indifferent between the (i) and null scenarios.

[b] The per capita CS is calculated using the compensation variation that makes representative consumers in each category of ranges indifferent between the (ii) and null scenarios.

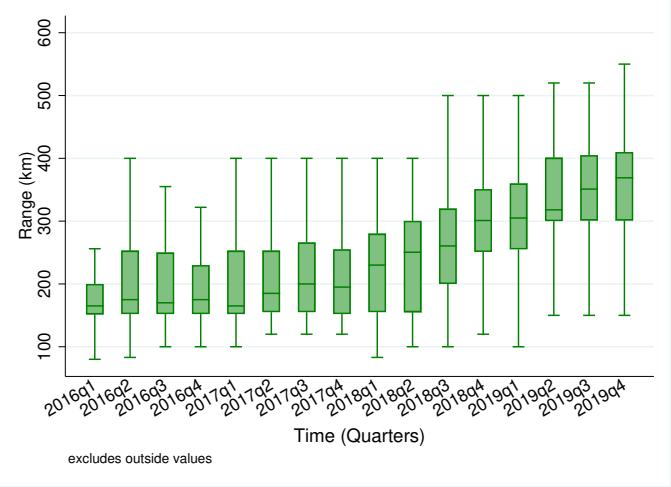
Figure 1: EV market structure over the sample period (2016-2019, quarterly)



(a) Number of EV manufacturers and models



(b) EV prices over time



(c) EV ranges over time

Figure 2: Cumulative number of EV chargers in the top 50 cities of EV sales (quarterly, 2016-2019)

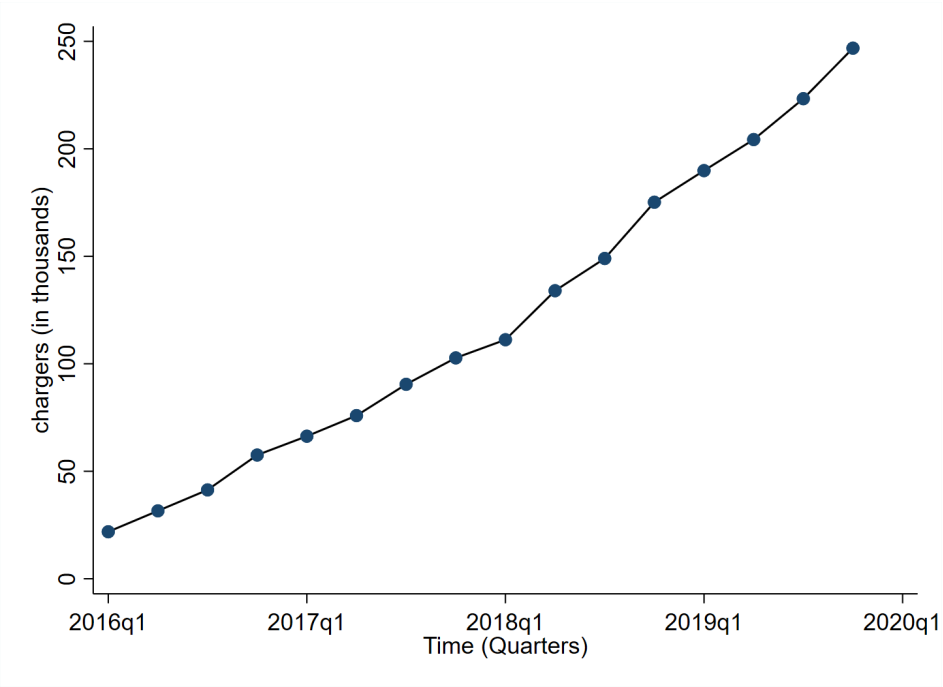
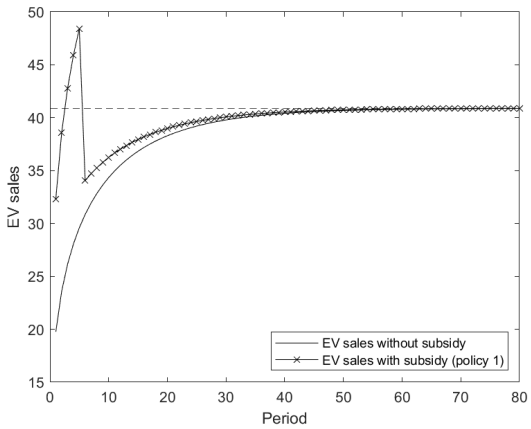
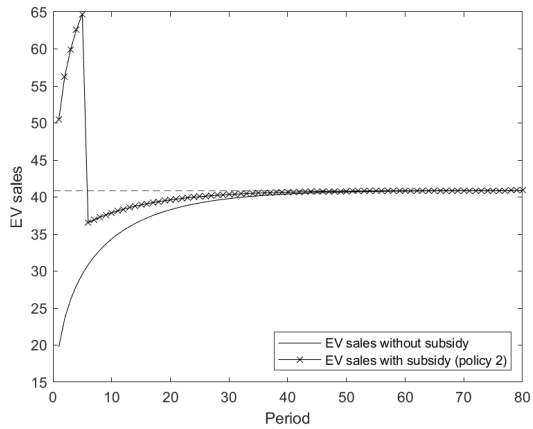


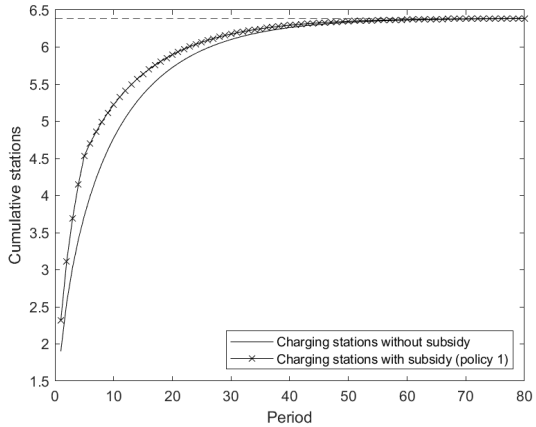
Figure 3: Indirect Network Effects and Subsidy Policies



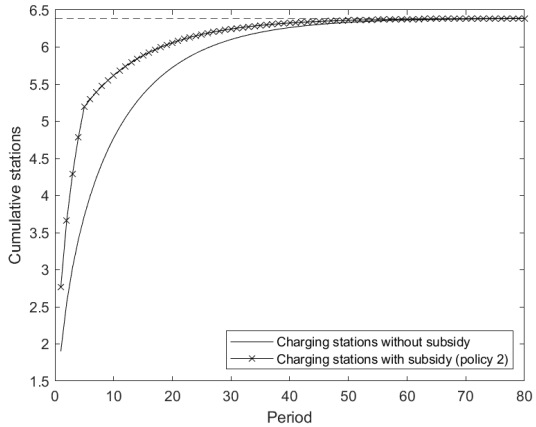
(a) EV sales (policy 1)



(b) EV sales (policy 2)



(c) Chargers (policy 1)



(d) Chargers (policy 2)

Figure 4: Policy Effectiveness and Electric Range

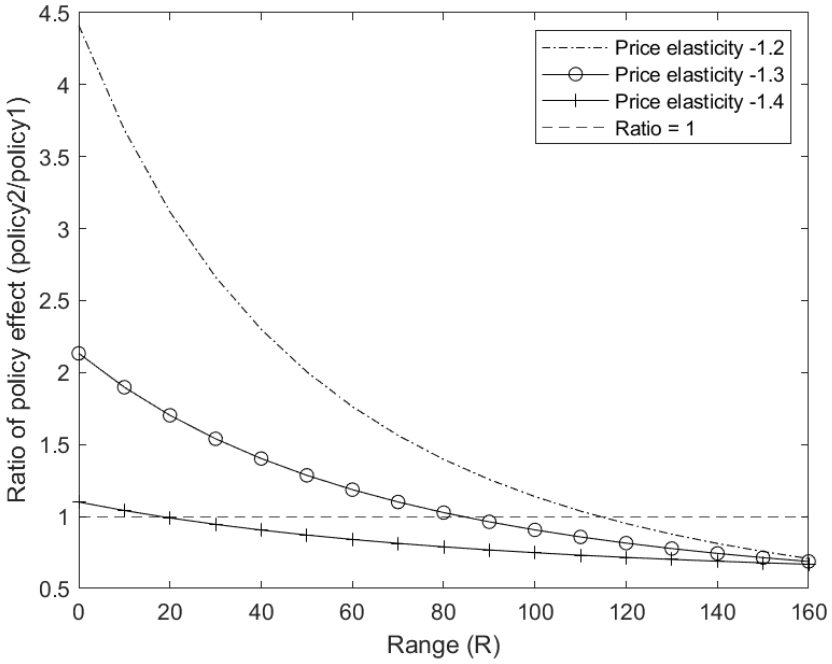


Figure 5: Per-period EV stock

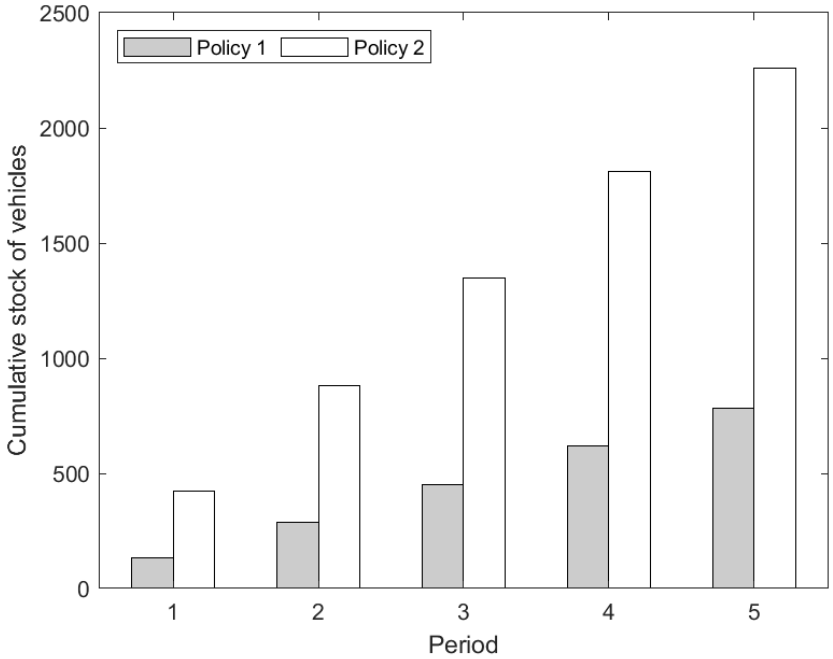


Figure 6: Share of High-range EVs

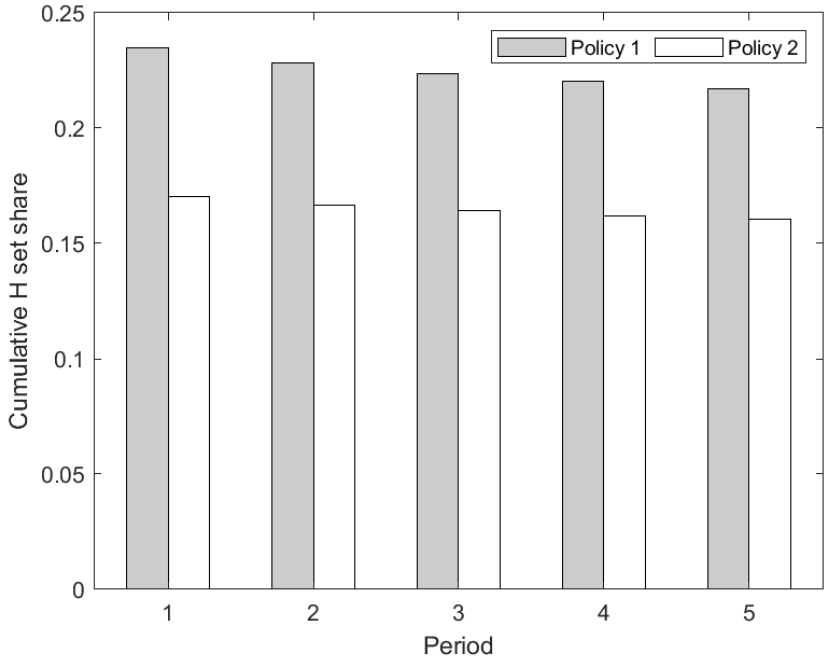
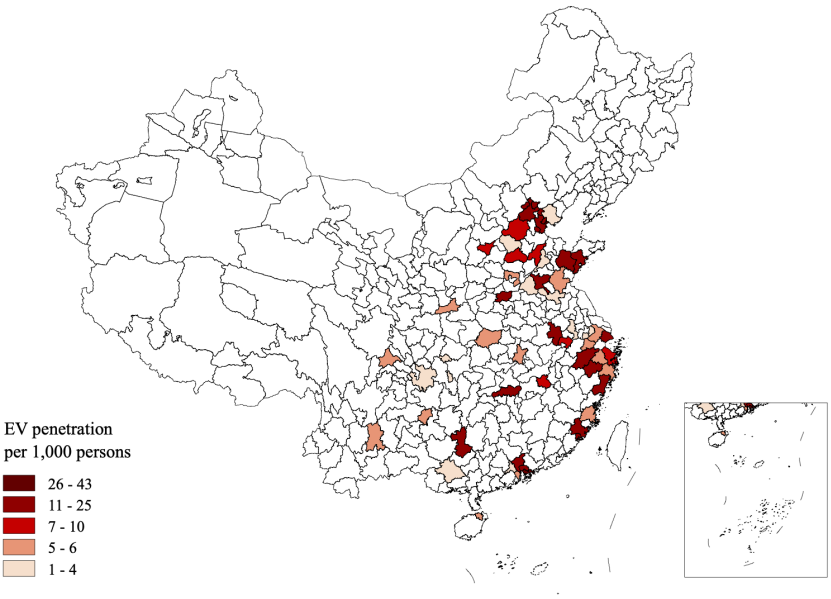
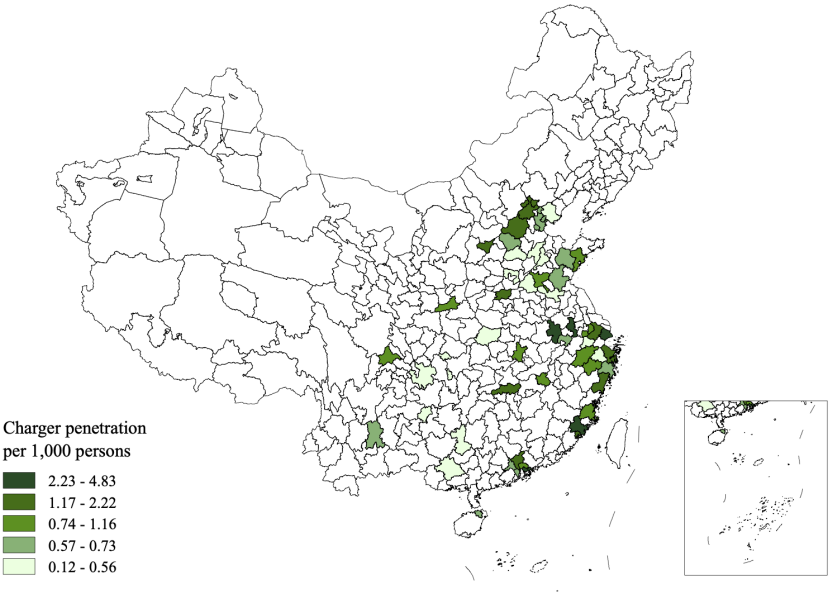


Figure 7: Penetration rates of EVs and public chargers per 1,000 persons in the sample cities



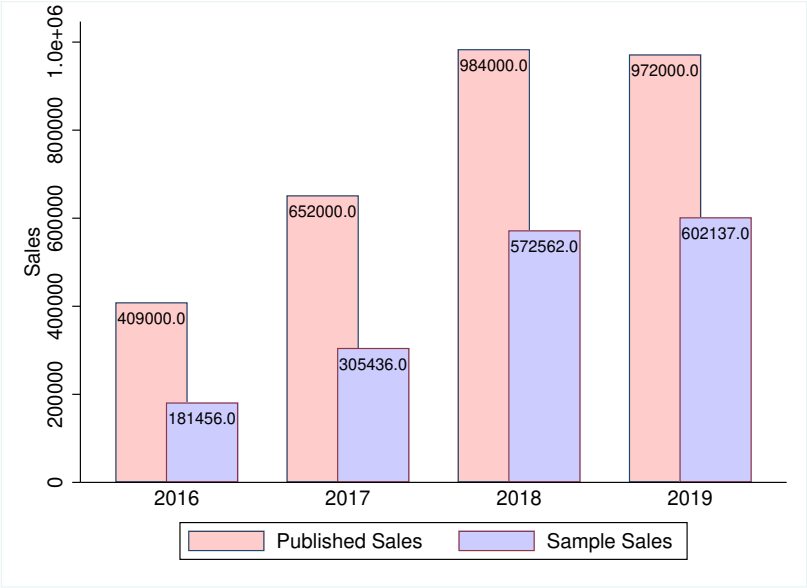
(a) EV penetration (2019)



(b) Charger penetration (2019)

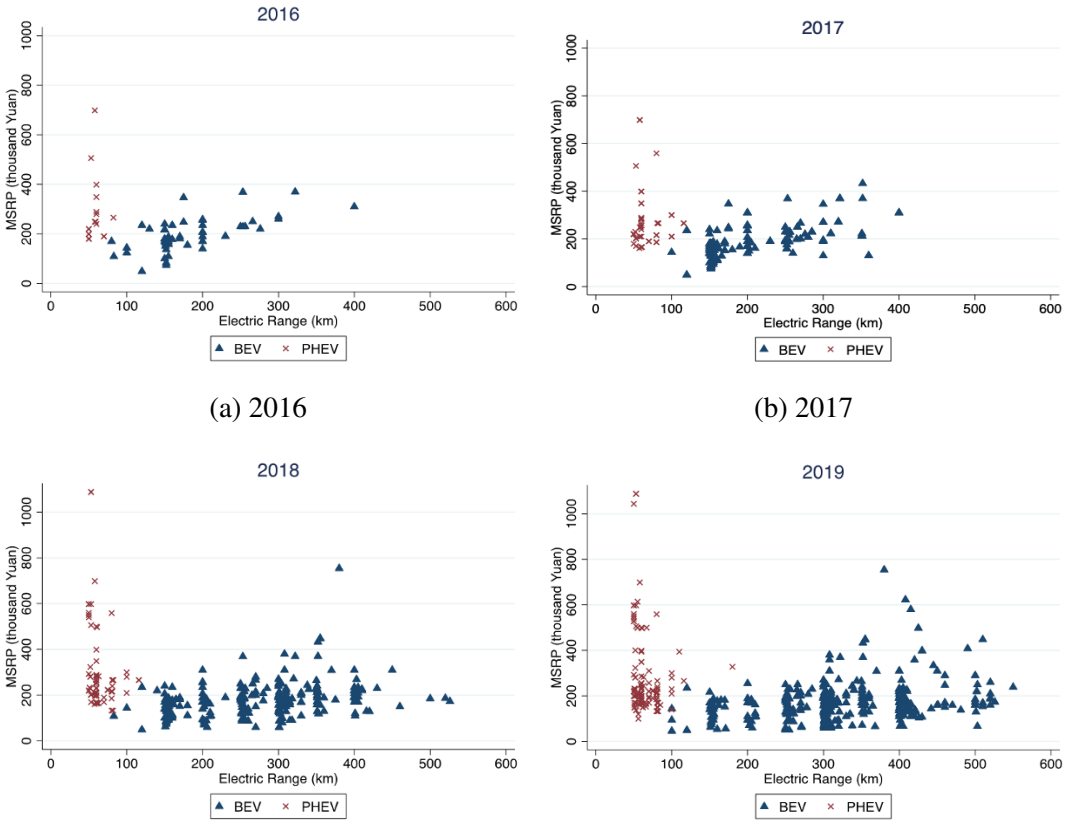
Notes: The penetration rates of EVs and chargers are calculated using the cumulative sales of EVs and supplies of chargers, respectively, over the 2016-2019 period.

Figure 8: Sample representativeness



Notes: The sample sales are the total of the top 50 cities in EV sales rankings. The published sales are the national total. The disparity between these two statistics reflects both the difference in statistical calibre and the sample selection.

Figure 9: EV price and driving range (2016-2019)



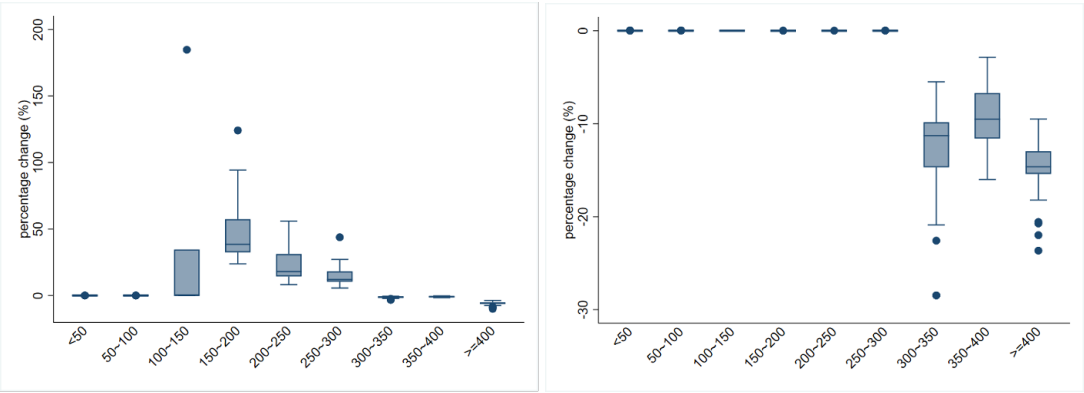
(a) 2016

(b) 2017

(c) 2018

(d) 2019

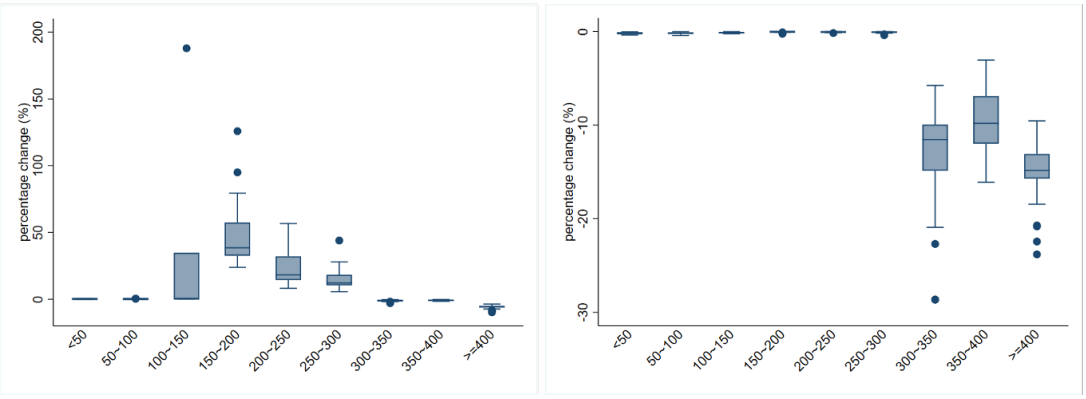
Figure 10: Effects of EV subsidies on EV sales by range



(a) Scenario (i) (b) Scenario (ii)

Notes: The boxplot indicates the distribution of the percentage changes in sales of EVs with ranges falling into the categories on the horizontal axis. The lower and upper boundaries of the box indicate the 25% and 75% quartiles of the distribution, respectively. The median is represented by a line subdividing the box. The length of the box represents the interquartile range (IQR) of the distribution. The upper and lower lines span the values within 1.5 IQR of the nearer quartile.

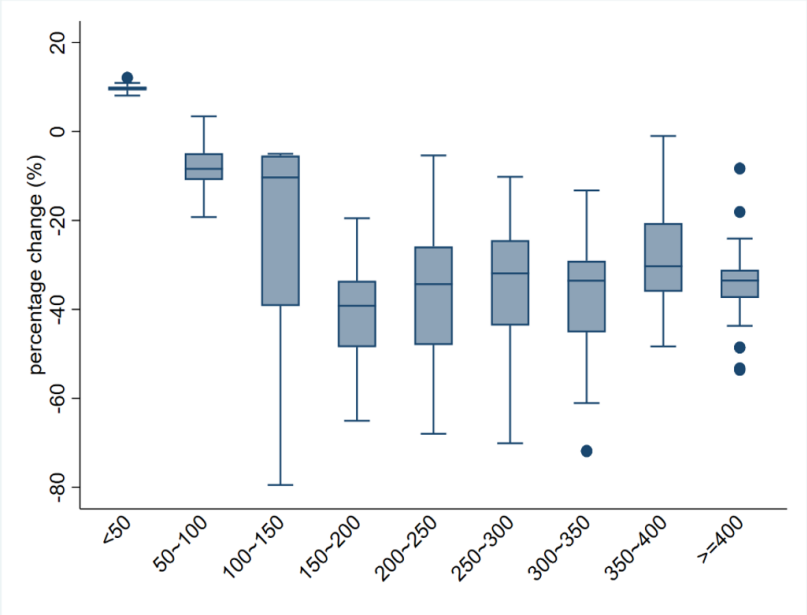
Figure 11: Effects of EV subsidies on EV sales by range (with indirect network effects)



(a) Scenario (iii) (b) Scenario (iv)

Notes: The boxplot indicates the distribution of the percentage changes in the sales of EVs with ranges falling in the categories on the horizontal axis. The lower and upper boundaries of the box indicate the 25% and 75% quartiles of the distribution. The median is represented by a line subdividing the box. The length of the box represents the interquartile range (IQR) of the distribution. The upper and lower lines span the values within 1.5 IQR of the nearer quartile.

Figure 12: Effects of charger subsidies on EV sales by range



Notes: The boxplot indicates the distribution of the percentage changes in sales of EVs with ranges falling in the categories on the horizontal axis. The lower and upper boundaries of the box indicate the 25% and 75% quartiles of the distribution. The median is represented by a line subdividing the box. The length of the box represents the interquartile range (IQR) of the distribution. The upper and lower lines span the values within 1.5 IQR of the nearer quartile.

Appendix A Infrastructure subsidies

Infrastructure subsidies vary across markets. We must standardize the subsidies with assumptions.

Assumption A-1 *Chargers are uniformly distributed over stations in each city and period.*

To calculate the number of chargers per station, we collect a subsample of the numbers of stations and chargers in each province for the period between November 2018 and December 2019,[1] and calculate the average number of chargers per station for province i[2] in each month t, π_{it}^{cs}. Then, we calculate the mean of this ratio over the subsample period for each province, $\bar{\pi}_i^{cs} = \sum_t \pi_{it}^{cs}$, and use it as the average number of chargers per station for that province.

Assumption A-2 *The composition of new AC and DC chargers is identical over stations in each city and period.*

Following this assumption, we calculate the proportions of AC/DC chargers of new chargers in each city in a given period.Since the entry numbers of chargers are unavailable but the cumulative number of chargers is observed in our sample, we calculate the entry numbers of chargers as follows. Denote the number of chargers of type x in city m by time t as $N_{m,t}^{c,x}$, where $x \in \{AC, DC\}$. Then, the number of newly established x chargers is $n_{m,t}^{c,x} = N_{m,t}^{c,x} - N_{m,t-1}^{c,x}$, and the probability that a charger will be x type is given by $\pi_{m,t}^{c,x} = \frac{n_{m,t}^{c,x}}{\sum_x n_{m,t}^{c,x}}$.

In some markets, the infrastructure subsidy also depends on the power of chargers. To standardize these power-based subsidies as charger-based subsidies, we need the following assumption.

Assumption A-3 *The distribution of charger power is identical over stations in each year.*

We collect the annual distribution of charger power at the national level for each year. [3] Denote the density of chargers of type x with power w_l^x in year Y as F_{lY}^x, and the mean power capacity of chargers is calculated by $\bar{w}_Y^x = \sum_l w_l^x F_{lY}^x$. Table A-2 presents the annual distribution of charger power at the national level over years.

Following the above assumption, we can convert various infrastructure subsidies into subsidies per charger. Assume the subsidy is based on power and type (x) of chargers and is denoted as $S_{it}^{c,x}$, where $x \in \{AC, DC\}$. Then, the average subsidy for each charger is given by $S_{it}^c = \sum_x \bar{w}_Y^x S_{it}^{c,x} \pi_{it}^{c,x}, \forall t \in Y$.

Another commonly observed case is that only the upper limits of station-based subsidies are known, while there is no information on subsidies on chargers of each type. In this case, we need the following assumption to calculate the upper limits of subsidies per charger.

Assumption A-4 *The latent upper limits of charger-based subsidies are consistent with the upper limits of station-based subsidies.*

This assumption warrants that following the proportions of AC and DC chargers per station, the expected upper limits of subsidies per station conditional on the latent upper limits of charger-based subsidies are consistent with the observed upper limits of station-based subsidies. Building on this assumption, no matter what the potential limits of charger-based subsidies are, the subsidy per charger is given by $S_{it}^c = \frac{S_{it}^s}{\bar{\pi}_i^{cs}}$, where $\bar{\pi}_i^{cs}$ is the average number of chargers per station, as discussed after assumption A-1. If

[1] The number of stations is available for this period only.

[2] We use subscript i to indicate the market, which is defined at the city level, in the main contents. To be consistent, we use a new subscript to indicate the province-level data. Finally, we match the province-level subsidies to the market (city)-level EV sales or station supply.

[3] Due to data limitations, local- or monthly-level distributions are unavailable.

a subsidy is based on stations of various types (x), we first convert it into a station-based subsidy using $S_{it}^{s} = \sum_x S_{it}^{s,x} \pi_{it}^{c,x}$; then, we calculate the charger-based subsidy by standardizing the station-based subsidy by $\bar{\pi}_i^{cs}$ as above.

Appendix B Marginal external cost

Our analysis of external costs focuses on pollution damage from vehicle fuel use or power generation. A comprehensive measure of the externalities of vehicle use should also measure nonpollution externalities, such as accidents, congestion and road damage costs. As one of the objectives of this paper is to investigate whether EV subsidies are a successful abatement policy, we focus on pollution externalities.

Parry et al. (2007) decompose the external cost of vehicle consumption into major components, such as greenhouse warming, local pollution, congestion and accidents in the US. They find that greenhouse warming and local pollution account for approximately 20% of the total external cost of vehicle driving. Parry et al. (2014) further estimate the external cost of vehicle consumption in China and reports the total marginal cost to be US $.55/liter for gasoline cars, reflecting combined damages from carbon and local pollution emissions, congestion, and accidents. Applying the shares of greenhouse warming and local pollution in marginal externalities in the US to the reported cost in China, we estimate the external cost of FV emission to be US $.11/liter. Parry et al. (2014) also report the corrective taxes for coal-fired power plants to be US $ 15/gigajoule (GJ) in China, reflecting combined damages from carbon and local pollution emissions. The Chinese government set the target of efficiency in coal consumption of coal-fired power units at 318 grams of standard coal equivalent per kWh and the target of transmission losses at 6.64%.[4] Accordingly, using these numbers, we can estimate the corrective taxes for coal-fired power plants to be $.154/kWh. [5] After taking into account the transmission losses, the external cost is US $.165/kWh (or RMB 1.155/kWh at an exchange rate of RMB 7/USD).

The corrective tax for natural-gas power plants is estimated to be US $3.2/GJ in China (Parry et al., 2014). Therefore, if there is a transition from coal-fired to natural-gas power generation in China, we expect the marginal external costs to be roughly 1/5 of the above estimates, or, US $ .0352/kWh (or RMB 0.246/kWh), which will significantly change the estimates of the total externalities.

Appendix C Tables

[4]Notice on the Issuance of the 13th Five Year Development Plan for Energy, by the NDRC and National Energy Administration, December 26, 2016.

[5]The conversion rate between the coal equivalent and GJ is 1 ton of coal equivalent = 29.3076 GJ, and the conversion rate between grams and tons is 1 ton = 907185 grams.

Table A-1: Market shares of above-scale (1,000) EV charging station operators in China

Company	Number of Chargers by Oct 2020	Market Share
Qingdao Teld New Energy	173395	26.0%
Star Charge	152728	22.9%
State Grid Corporation of China	144270	21.6%
Jiangsu YKC New Energy Technology	50726	7.6%
EV Power	25566	3.8%
AnYo Charging	19762	3.0%
Potevio	14293	2.1%
Shenzhen Car Energy Network	14084	2.1%
Zhejiang Wanma New Energy	11337	1.7%
Winsky New Energy	8309	1.2%
Echarging New Energy (Shenzhen)	6118	0.9%
Zhuhai EV-Link New Energy Vehicles	5409	0.8%
Shanghai Zhida Technology Development	5179	0.8%
NanJing NengRui Power Science and Technology	4693	0.7%
Guangdong Thousands of Cities & Charging Stations(TCCS) E-Vehicles Operating	4364	0.7%
EVchong	3911	0.6%
Tesla	2492	0.4%
Unite Quick Charge	2170	0.3%
China Southern Power Grid	2118	0.3%
Balance Power (Shanghai) Industrial	2087	0.3%
GuangDong JinTian Technology	2011	0.3%
Shenzhen Costar Smart Technology	1718	0.3%
Beijing Tellus Power Green Energy	1534	0.2%
Sinocharge	1487	0.2%
NIO	1482	0.2%
BYD	1210	0.2%

Table A-2: National distribution of charger power in the sample period

Year	Power (kw)	Percentage
	DC charging stations	
2016	60	27.82%
	30	25.08%
	120	12.88%
	150	8.97%
2017	60	28.68%
	150	23.39%
	120	12.12%
	30	12.05%
2018	60	26.96%
	120	25.36%
	150	21.04%
	180	6.20%
2019	120	33.05%
	150	29.79%
	60	15.18%
	180	5.87%
	AC charging stations	
All years	7	100%

Table A-3: Results of the estimation of the charger supply function with lagged subsidies

	OLS				TSLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$log(N_{mt}^{EV})$	0.927***	0.331***	0.923***	0.330***	1.111***	0.873***	1.116***	0.837***
	(0.076)	(0.097)	(0.077)	(0.094)	(0.111)	(0.255)	(0.108)	(0.250)
$log(subsidy_t)$ $(log(SC_{mt}^c))$	0.168***	0.050**	0.129***	0.045**	0.150***	0.053**	0.114**	0.047**
	(0.050)	(0.020)	(0.040)	(0.017)	(0.053)	(0.022)	(0.043)	(0.019)
$log(subsidy_{t-1})$ $(log(SC_{m,t-1}^c))$	0.172***	0.042**	0.111***	0.033**	0.156***	0.048**	0.100***	0.036**
	(0.046)	(0.020)	(0.031)	(0.014)	(0.048)	(0.020)	(0.032)	(0.014)
$log(subsidy_{t-2})$ $(log(SC_{m,t-2}^c))$			0.116***	0.022			0.106***	0.026
	(0.666)	(0.831)	(0.031)	(0.016)			(0.032)	(0.016)
Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	2303	2303	2254	2254	2303	2303	2254	2254
First-Stage F-statistics					346.69	98.45	361.81	98.80

Standard errors in parentheses. * p<0.10, ** p<0.05, and *** p<0.01