https://doi.org/10.1016/j.jclepro.2019.119479

The Potential Influence of Cost-Related Factors on the Adoption of Electric Vehicle: An Integrated Micro-Simulation Approach

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Abstract

Cost-related factors (e.g., subsides) play a vital role in the diffusion of Electric Vehicle (EV). However, it remains unclear how these factors would influence the diffusion and further the associated urban elements (e.g., infrastructures) at the micro scale. In response, this paper tried to quantify the influence of two types of cost-related factors on the adoption of Electric Vehicle (EV), namely upfront cost and usage-related cost, using purchase subsides and fuel prices as examples, respectively. An agent-based integrated micro-simulation model (SelfSim-EV) was used here to simulate how the EV market in Beijing might evolve from 2016 to 2020, within several "what-if" scenarios considering different Plug-in Hybrid Electric Vehicle (PHEV) subsides, petrol prices and electricity prices. The results suggested that 1) doubling the PHEV subsidy would make PHEV price competitive and thus increase the PHEV sale from around zero to 2,500 in 2019. The PHEV sale price increases by around 3,500 RMB (from around 261,000 to 264,500 RMB) due to the increase in the PHEV penetrate rate. This further gives rise to the changes in those urban elements connected with the EV market, including the urban environment, electricity and infrastructure systems, especially at the disaggregate level; 2) both electricity and petrol prices have little influence on the adoption of EVs at the macro level (i.e. the city level), but they do influence the spatial distributions of both CV and EV owners (based on the analyses of their residential locations) and further geographical distributions of vehicular emissions, EV-related facilities (e.g., charging posts) and electricity demand of EV at multiple resolutions, ranging from the facility level to district level.

Keywords: Electric Vehicle; Subsidy; Petrol Price; Electricity Price; Agent-based Model; Impact Assessment

1 Introduction

As one of the most popular alternative fuel vehicles, Electric vehicle (EV), including Battery Electric Vehicle (BEV) and Plug-in Hybrid Electric Vehicle (PHEV), has received increasing attention over the past few years, as partly evident from the rising penetration rate of EV in many countries across the global. As indicated in the recent report of "Global EV Outlook 2018" (Bunsen et al., 2018), the global stock of EV reached 3.1 million in 2017 with an increasing rate of 57%. The number of EVs sold in 2017 was over 1 million, and more than half of them were sold in China. In terms of the EV market share, Norway, Iceland and Sweden ranked top three with penetration rates of 39.0%, 11.7%, and 6.3%, respectively. China came fourth with a rate of 2.2%. In order to promote the development of EVs, many regulations and approaches have been used. For example, in the Nordic region (where the EV market share is amongst the highest globally), several policies, such as purchase incentives, use incentives and waivers on access restrictions, have been used at both local and national levels (IEA, 2018). Similarly, both the central and local governments in China had several EV policies (e.g., subsidies and traffic regulations) in place, in order to promote both the purchase and use of EVs (Hao et al., 2014; Zhuge and Shao, 2019).

In general, Conventional Vehicle (CV), such as petrol and diesel cars, are associated with environmental issues, such as air pollution (Zhang and Batterman, 2013), greenhouse gas (GHG) emissions (Hao et al., 2011) and wastewater. This further requires different sustainable methods, such as nitrifying-enriched activated sludge (NAS) approach (Sepehri and Sarrafzadeh, 2018), to directly or indirectly deal with these wastes. However, EV is expected to bring great environmental benefits. For example, BEV runs on electricity and thus do not release any vehicular emissions when moving around the cities, which can improve local air quality and bring health benefits (Buekers et al., 2014). At the global level, the introduction of EV has great potential to reduce GHG emissions, but the net reduction is associated with the electricity mix (Casals et al., 2016); Another related benefit of BEV is the reduction in noise pollution: the extent to which the introduction of EV could reduce noise is associated with travel speed. It was found that the reduction is limited when EVs move at a speed above 50 km/h, due to rolling noise (Campello-Vicente et al., 2017).

Whether a consumer would purchase an EV could be influenced by a wide variety of factors, as recently reviewed in (Biresselioglu et al., 2018; Hardman et al., 2017; Li et al., 2017). Those cost-related factors associated with the purchase and use of EV (e.g., subsidies and free parking) were identified as influential to the diffusion of EVs (Zhuge et al., 2019d). For example, the recent report by the International Energy Agency (IEA) on the development of EV in the Nordic region suggested that lowering EV sale price was proved to be the main cause of the rising EV market share (IEA, 2018). This paper will investigate the role of the cost-related factors in both the purchase and use of EVs, using EV subsides and energy prices as examples, respectively. Specifically, an agent-based urban micro-simulation model, SelfSim-EV (Zhuge et al., 2016; Zhuge et al., 2019d), will be used to simulate how people respond to different PHEV subsidies, electricity prices and petrol prices within several “what-if” scenarios, considering the interactions between the diffusion of EV and those associated urban sub-systems (e.g., transportation, land use, and population systems). Based on the simulations, the potential influences of these cost-related factors on the EV diffusion and the associated urban sub-systems can be quantified. Furthermore, the simulation results are spatially explicit. This means various spatial analyses of the EV diffusion can be conducted subsequently, providing insights into the potential influences at the disaggregate level. These kinds of systematic and spatially disaggregate analyses have received scant attention in the previous studies investigating the cost-related factors. These research gaps will be elaborated later in Section 2.

The remaining sections are structured as follows: Section 2 will review the existing literature on both the upfront cost reduction and usage-related cost reduction in the EV purchase, identifying the research gaps to fill in this paper; Section 3 will introduce the agent-based integrated urban model (SelfSim-EV), and also describe how it will be used to investigate the role of different cost-related factors in the EV diffusion within “what-if” scenarios; Section 4 will present both disaggregate and aggregate results from the scenarios, providing insights into the potential influences the cost-related factors on the EV market expansion and the associated urban sub-systems; Section 5 will discuss how the results could be further used in policy making and infrastructure planning and optimization for EVs; In Section 6, this paper will conclude with a summary of the key findings and the future work.

2 Literature Review

2.1 Upfront Cost Reduction

In order to reduce the high upfront cost of EV, financial incentives, such as purchase subsidies and tax exemption, appear to one of the most-used strategies to incentive early EV adopters (Bjerkan et al., 2016; Zhuge and Shao, 2019). As a result, EV could become price competitive and thus favourable (Hao et al., 2014).

(1) EV Subsides

The influence of EV subsides on the uptake of EV varied from case to case, and could be either significant or marginal.

Many studies suggested that subsides could be effective in promoting the purchase of EV (Coad et al., 2009; Hao et al., 2014; Lieven, 2015; Sierzchula et al., 2014; Wang et al., 2017). Some specific examples are as follows: Sierzchula et al. (2014) explored the relationship between the EV subsidy and EV market share in 30 countries across the world, suggesting that subsidy was a statistically significant variable; Hao et al. (2014) argued that EV subsides in China were very necessary for BEVs to be cost competitive compared with CVs, especially at the early stage of the EV development; Lieven (2015) also found subsides as attractive, though a combination of lower subsidy and easy access to charging facilities could also result in similar preference shares.

However, some studies suggested that subsidy was not as influential as generally expected. Helveston et al. (2015) explored the role of subsides in the uptake of EV in both the USA and China and found that subsides did not change preference order in either country; Based on an expert workshop with policy-makers, Bakker and Trip (2013) argued that subsides were generally costly and might not be effective: on one hand, EV could still remain too expensive to the majority of potential customers; on the other hand, vehicle manufacturers might not want to lower their vehicle sale prices.

(2) Tax Exemption or Rebate

Tax exemption or rebate is another typical type of financial incentive to reduce the upfront cost. A quantitative assessment of the tax rebate by Chandra et al. (2010) in Canada suggested that 26% of the EV sold could be attributed to the rebate. Similarly, Bjerkan et al. (2016) surveyed around 3400 BEV owners in Norway and found that more than 80% of them considered exemptions from purchase tax and VAT as critical incentives. Furthermore, a comparative study of eight European countries by Lévay et al. (2017) suggested that "the exemption from the flat tax rates would promote the adoption of big expensive EVs in Norway and the Netherlands".

(3) Methods and Models Used

A variety of models and methods have been used to investigate the influence of EV subsidies and tax exemption/rebate on the adoption of EV, including discrete choice models (e.g., MNL (Helveston et al., 2015; Lieven, 2015) and Mixed Logit (Helveston et al., 2015; Langbroek et al., 2016)), regression model (Chandra et al., 2010; Gallagher and Muehlegger, 2011) (e.g., ordinary least squares (OLS) regression (Sierzchula et al., 2014) and standard linear regression (Mersky et al., 2016)) and agent-based models (Eppstein et al., 2011; Noori and Tatari, 2016). Among them, agent-based modelling has been increasingly viewed as a promising approach to simulating consumer energy choices, including choices of EV (Rai and Henry, 2016) because of its advantages (e.g., heterogeneity). Therefore, this paper will use agent-based modelling as well.

2.2 Usage -Related Cost Reduction

Apart from upfront cost reduction, several other methods have been used to reduce the usage-related cost, such as free parking (Langbroek et al., 2016; Lieven, 2015) and exemption from road tolling (Lieven, 2015). Their influences on the EV adoption vary from case to case: Langbroek et al. (2016) found free parking as a positive influential factor, while Lieven (2015) found that the free use of downtown parking was not attractive. Both Lieven (2015) and Mersky et al. (2016) found free use of fast lanes was not attractive or statistically significant; while Bjerkan et al. (2016) found that "exemption from road tolling or bus lane access was the only decisive factor to a considerable number of EV owners".

Fuel cost is another type of the usage-related cost. Since EV drivers could save fuel cost by using electricity and thus could reduce the usage-related cost, several studies have investigated whether fuel price is an influential factor to the EV adoption. Some of them suggested that fuel price had relationship with the adoption of EV (or EV sale) (Beresteanu and Li, 2011; Chandra et al., 2010; Diamond, 2009; Eppstein et al., 2011; Gallagher and Muehlegger, 2011). For example, Gallagher and Muehlegger (2011) found that the rising gasoline prices were associated with the increase of EV sale. However, most of them only looked at the gasoline prices, paying almost no attention to electricity price. This paper attempts to investigate the influence of both petrol and electricity prices on the EV adoption, as well as its further influences on those connected urban elements (e.g., transportation and land use systems), which have received scant attention in the previous studies.

2.3 Research Gaps

As reviewed above, several strategies have been used to reduce both upfront cost and usage-related cost, in order to make EVs cost competitive and to promote the purchase and use of EVs. However, the existing studies examining the cost-related factors have tended to pay no or little attention to the connections or interactions between the EV market and those connected urban elements, such as the urban environment, electricity system and EV-related facilities (Zhuge et al., 2019d). As a result, only a limited understanding of the EV adoption can be obtained for the EV-related stakeholders, such as the government and manufactures. For example, local authorities generally hope to gain full insights into the influence of a specific policy, not only on the uptake of EVs, but also on the environment, transport, land use and energy systems. In addition, most of the existing studies have tended to analyse the influences of the cost-related factors from a statistical perspective. As a result, little is known about the influence on the spatial characteristics of the EV market and its connected urban elements. In response, this paper would pay equal attention to the spatial and statistical analyses, as the spatially disaggregate results would be particularly useful for identifying the hot spot of charging demand of EVs, and thus could help better deploy and optimize EV-related facilities in both transport and power sectors.

In order to fill the two research gaps above, we used an agent-based spatial urban model, SelfSim-EV (Zhuge et al., 2019d), to examine the potential influences of two typical cost-related factors, namely PHEV subsidies and energy prices. Based on the SelfSim-EV simulation, on one hand, both the expansion of EV market and its impacts on those connected urban systems can be explored; on the other hand, various spatial analyses of the EV market can be further carried out. Such comprehensive and spatially explicit results are expected to provide the EV-related stakeholders with full information on the diffusion of EV.

3 Methodology

3.1 Brief Introduction to SelfSim-EV

As aforementioned, we will use an agent-based integrated micro-simulation model, SelfSim-EV, to explore the role of the cost-related factors in the adoption of EV. The reasons are twofold: 1) the model is capable of simulating both the purchase and travel behaviours of EV, considering the interactions between the EV market and those connected urban systems (e.g., transportation and land use) over time at the micro scale; 2) the model has been calibrated and validated in a real-world scenario set up based on Beijing, which can be used as a baseline in this paper to help understand how the cost-related factors may influence (Zhuge et al., 2019d).

As shown in Figure 1, SelfSim-EV contains a set of spatial urban models that can run in a specific sequence for the micro-simulation of urban evolution, involving in the purchase behaviour of EV (in the EV Market Model), individual travel behaviour of EV (in the Activity-based Travel Demand Model), the development of EV-related transport facilities (in the Transport Facility Development Model), the changes in socio-demographic characteristics (in the Demographic Evolution Model), residential location choice of household (in the Joint Model of Residential Location Choice and Real Estate Price, RLC-REP) and social ties (in the Social Network Evolution Model) (Zhuge et al., 2019d). In brief, SelfSim-EV is an integrated urban microsimulation platform incorporating the purchase and use behaviours of EV, as well as the EV-related behaviours, actions and decision-makings of agents.

More detailed introduction to SelfSim-EV and its key components (e.g., transport facility development model) can be found in the work of (Zhuge and Shao, 2018a; Zhuge and Shao, 2018b; Zhuge et al., 2018a; Zhuge et al., 2018b; Zhuge et al., 2019c; Zhuge et al., 2019d). The introduction to the datasets for the model initialisation and calibration can be found in (Zhuge and Shao, 2019; Zhuge et al., 2019a; Zhuge et al., 2019b; Zhuge et al., 2018a; Zhuge et al., 2018b).

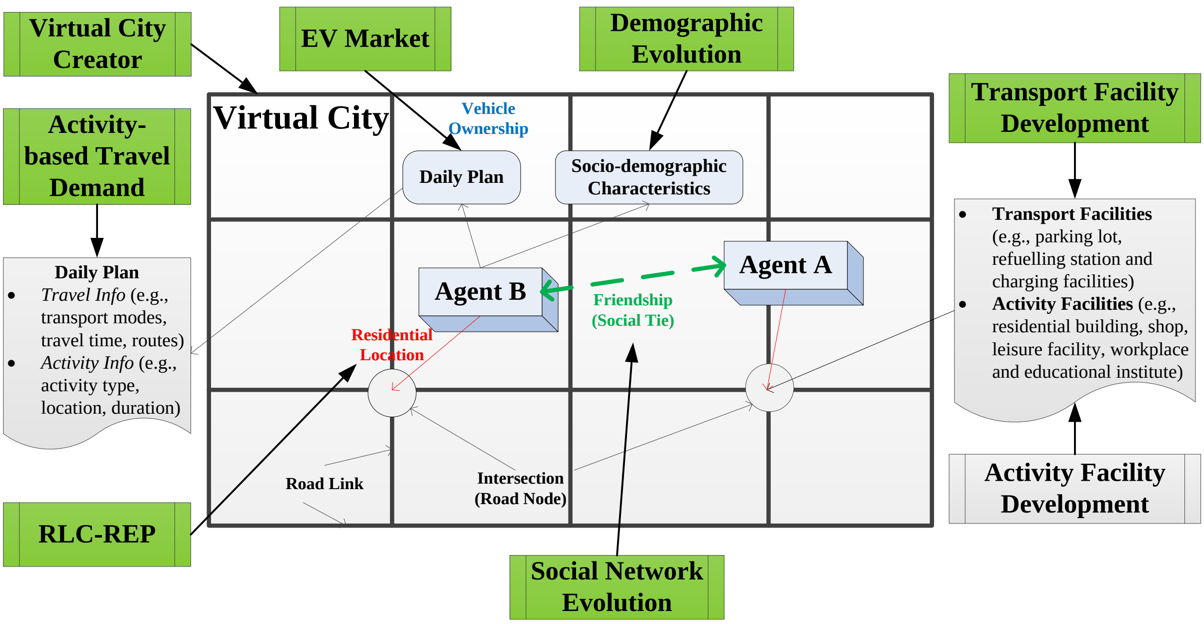


Figure 1 Sketch of Urban Dynamic Simulation within SelfSim-EV (Source: Adapted from (Zhuge et al., 2018a))

3.2 "What-If" Scenario Analysis within SelfSim-EV

In order to investigate how different PHEV subsides and fuel prices may influence the adoption of EV and further its connected urban elements within "what-if" scenarios, the PHEV subsidy and fuel price need to be particularly specified within the SelfSim-EV model prior to a simulation. These two factors are associated with the decision-making of consumer agents in the EV market model, which is simulated with a utility function (see Equation (1)). Specifically, it is assumed that consumer agents always choose the vehicle type which can maximum their own utilities ($U_{VehicleChoice}$). The utility function, which was developed based on the empirical study of (Zhuge and Shao, 2019), is composed of five terms, namely social influence ($U_{SocialInfluence}$), daily plan ($U_{DailyPlan}$), purchase price ($U_{PurchasePrice}$), environmental benefit ($U_{Environment}$) and randomness (U_{Random}) (Zhuge et al., 2019d). The PHEV subsidy and fuel price are considered in the utility function as follows:

1) PHEV Subsidy: is considered in the utility term for purchase price ($U_{PurchasePrice}$). Specifically, Due to the PHEV subsidy, the potential consumers will pay less for PHEVs and therefore have higher utility of purchase price ($U_{PurchasePrice}$).

2) Fuel Price (either Petrol or Electricity Prices): can be set in the utility term of daily plan ($U_{DailyPlan}$) which can be further decomposed into utilities of daily activity ($U_{DailyActivity}$) and travel (U_{Travel}), as shown by Equation (2). People can gain utilities through performing their daily activities (e.g., shopping) and lose utilities because of travelling from one activity location to another (Horni et al., 2016). The fuel price, together with travel distance, will be used to calculate the travel cost for each driver with either CV or EV. Therefore, fuel price can influence the utility of daily plan ($U_{DailyActivity}$) and further the choice behaviour of consumer agents in the vehicle market.

$$U_{VehicleChoice} = U_{SocialInfluence} + U_{DailyPlan} + U_{PurchasePrice} + U_{Environment} + U_{Random} \quad (1)$$

$$U_{DailyPlan} = U_{DailyActivity} + U_{Travel} \quad (2)$$

4 Case Study of Beijing

4.1 Overview of Scenarios

SelfSim-EV has been applied to Beijing to simulate its EV market from 2016 to 2020 within a so-called Reference Scenario (RefSc), with the assumption that the Beijing urban system (including the EV market and the connected urban systems) would evolve as before: more details on the EV market in RefSc and its possible influences on the urban environment, electricity system and EV-related facilities can be found in (Zhuge et al., 2019d). Therefore, Beijing was used a case study here again to explore how different cost-related factors, including PHEV subsides (Scenario A, see Section 4.2), petrol prices (Scenario B, see Section 4.3) and electricity prices (Scenario C, see Section 4.4), might influence the uptake of EVs within several “what-if” scenarios, compared to RefSc (or the baseline).

Therefore, the results from the RefSc scenario, as detailed in (Zhuge et al., 2019d), will be cited below in order for comparison purpose. In addition, the calibrated and validated SelfSim-EV Beijing model (Zhuge et al., 2019d) will be modified as described in Section 3.2, in terms of the PHEV subsides, electricity prices and petrol prices, in order to set up the "what-if" scenarios.

4.2 Scenario A - PHEV Subsidies

4.2.1 Description of Scenario A

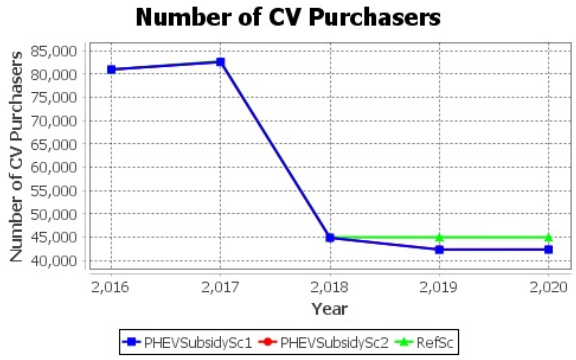
The PHEV purchasers in Beijing were only offered the national subsidy in 2015, and the Beijing government did not provide them with any local financial incentives. This could be one reason that PHEVs did not sell well in 2014 and 2015, compared with BEV sales. The scenarios here aim to explore the future of EVs in Beijing, given that the PHEV purchasers will receive subsidies from both the Beijing and national governments from 2016 to 2020. Since 2014, the Beijing government has provided the same amount of BEV subsidy as the national government. Therefore, the scenarios for PHEV subsidy here assume that the PHEV purchasers will also receive extra subsidy which is equal to the amount of subsidy provided by the national government. Specifically, the scenarios are set up as follows:

- **PHEV Subsidy Scenario A1 (PHEVSubsidySc1):** the PHEV subsidy will double in 2016 because of the extra subsidy form the Beijing government and will not change over the period from 2016 to 2020.
- **PHEV Subsidy Scenario A2 (PHEVSubsidySc2):** the PHEV subsidy will double in 2016 and may change over the period, according to the behavioural rules of the government. In the EV market model, it is defined that the government agent updates EV subsides according to the adoption rate of EVs, as detailed in (Zhuge et al., 2019d).

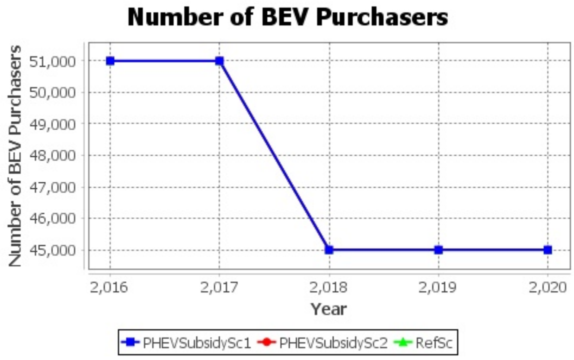
4.2.2 The Influence of PHEV Subsidy on the EV Market Expansion

Figure 2 compares the EV markets from 2016 to 2020 in the three different scenarios, namely Reference Scenario (RefSc), PHEV Subsidy Scenario A1 (PHEVSubsidySc1) and PHEV Subsidy Scenario A2 (PHEVSubsidySc2), in terms of vehicle sale, vehicle price and EV subsidy. Note that the RefSc is cited from (Zhuge et al., 2019d) for comparison purpose. Overall, adding extra PHEV subsidy can promote the PHEV sales after 2018 when the BEV price goes up due to the increase in the BEV penetration rate, which makes PHEV more competitive in terms of final price (that is the difference between the PHEV subsidy and the original PHEV selling price), compared with BEV. As a result, the number of PHEV purchasers goes up from around zero to 2,500 and the number of CV purchasers decreases by around 2,500, due to the constraint on the total number of CV purchase permits. Meanwhile, the PHEV and CV prices go up and down, respectively, according to the change in their penetration rates. Specifically, the PHEV sale price increases by around 3,500 RMB (from around 261,000 to 264,500 RMB), and the CV sale price decreases by around 2,000 RMB (from around 128, 000 to 126, 000 RMB). In addition, the small difference between PHEVSubsidySc1 and PHEVSubsidySc2 in the EV market expansion suggests that the government agent changes slightly the PHEV subsidies over the period in order to keep PHEVs price comparative.

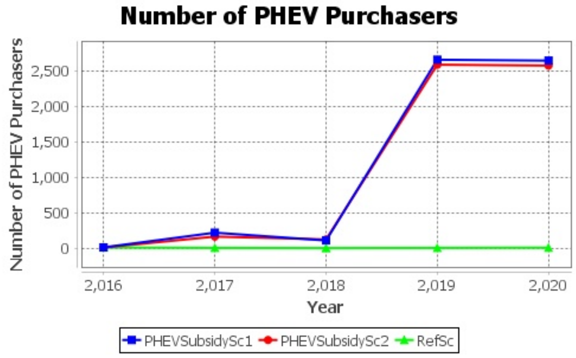
The analyses above suggest that the PHEV subsides influence the EV market expansion through the interactions among the consumer, vehicle manufacturer and government agents in a dynamic way. Specifically, doubling PHEV subsides in 2016 has almost no influence on the vehicle market, and it starts to influence consumer agents when the BEV manufacturer agent increases the BEV sale price in 2018, which makes the PHEV competitive in terms of final purchase price. On the other hand, this suggests that the agent-based EV market model is useful here for capturing such interactions at the individual level over time.



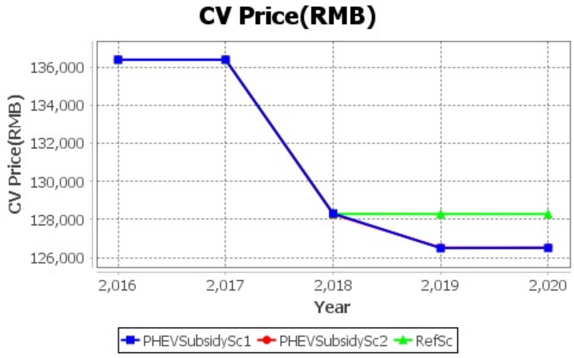
(a) CV Sale
(PHEVSubsidySc1 Overlaps PHEVSubsidySc2)



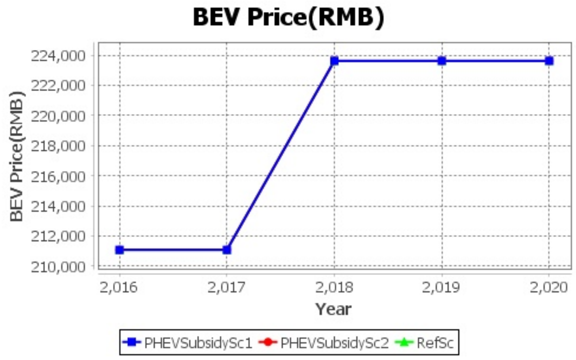
(b) BEV Sale



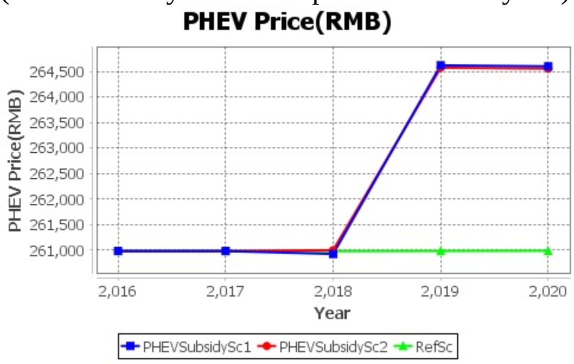
(c) PHEV Sale



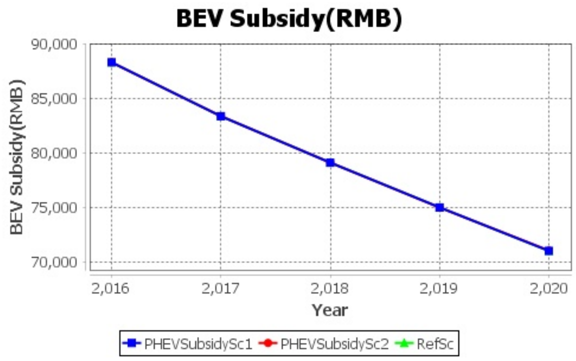
(d) CV Sale Price
(PHEVSubsidySc1 Overlaps PHEVSubsidySc2)



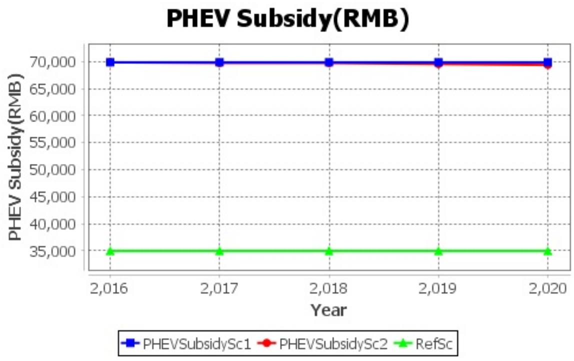
(e) BEV Sale Price



(f) PHEV Sale Price



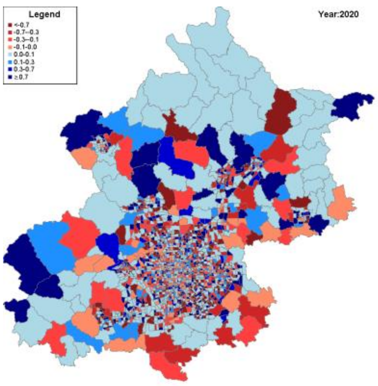
(g) BEV Subsidy



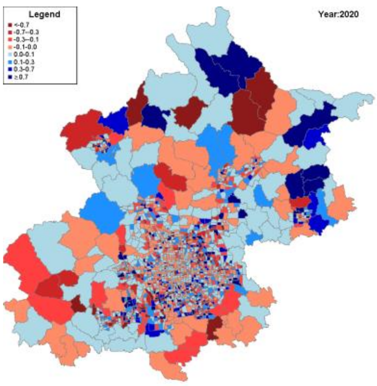
(h) PHEV Subsidy

Figure 2 Differences between "What-If" and RefSc Scenarios in Vehicle Sale, Vehicle Price and EV Subsidy from 2016 to 2020 (Note: the RefSc is cited from (Zhuge et al., 2019d))

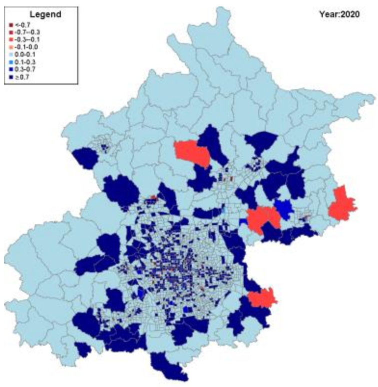
As show by Figure 3, increasing the PHEV subsidies in both scenarios can significantly influence the spatial distributions of CV, PHEV and BEV owners in 2020 at the traffic zone- level, based on their residential locations. Specifically, the rise of PHEV subsidy could either increase or decrease the numbers of BEV and CV owners in different traffic zones; while the rise nearly increases the number of PHEV owners to the majority of the traffic zones, which is very likely due to the increase in the number of PHEV purchasers (see Figure 2-(c)). More details on the spatial differences in vehicle owners at the facility- and district- levels can be found in Supplementary Material (see Figure A1 and Figure A2, respectively). The spatial changes in EV owners can influence charging demand in terms of both quantity and spatial distribution. Specifically, different vehicle owners could have completely different travel patterns (e.g., trip destinations, durations and departure time), which could result in different vehicle miles travelled, amounts of electricity consumed and charging demands.



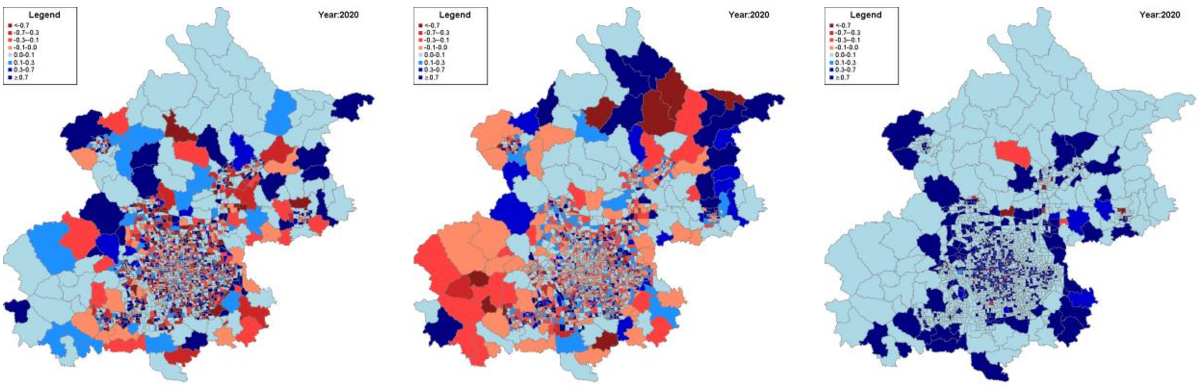
(a) BEV Owners in PHEVSubsidySc1



(b) CV Owners in PHEVSubsidySc1



(c) PHEV Owners in PHEVSubsidySc1

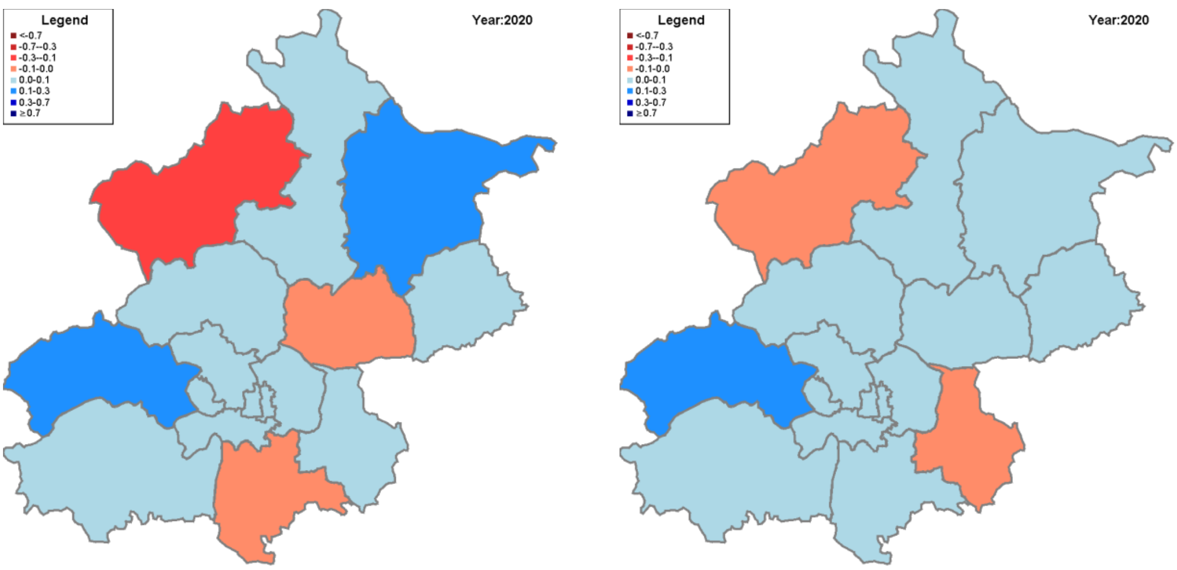


(d) BEV Owners in PHEVSubsidySc2 (e) CV Owners in PHEVSubsidySc2 (f) PHEV Owners in PHEVSubsidySc2

Figure 3 Differences between "What-If" and RefSc Scenarios in the Residential Location of Vehicle Owner in 2020 at the Traffic Zone Level (Zhuge et al., 2019d)

4.2.3 The Influence of PHEV Subsidy on the EV-related Infrastructures

At the aggregate level, adding extra PHEV subsidy appears to have little impact on the number of EV-related infrastructures, including public parking lots and public charging posts (see Figure A3 in Supplementary Material). Among them, only public charging posts increase marginally when the subsidy is doubled due to the increase in the number of PHEV purchasers. However, the changes in PHEV subsidy could to some extent influence the layout of public charging posts at the district level (see Figure 4), and the outer districts appear to be more influenced than the central districts. In such a complex and dynamic system, the layout of public charging posts could be influenced by several factors. For example, the spatial changes in vehicle owners (see Figure 3) could result in completely different travel patterns, which could further lead to the changes in charging demand and then the demand for charging facilities.



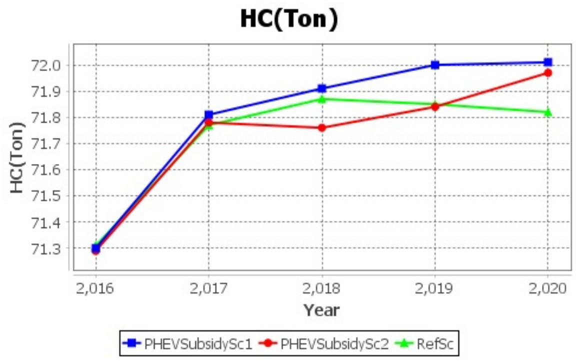
(a) Diffeence betwene PHEVSubsidySc1 and RefSc (b) Difference between PHEVSubsidySc2 and RefSc

Figure 4 Differences between "What-If" and RefSc scenarios in the District-Level Layout of Public

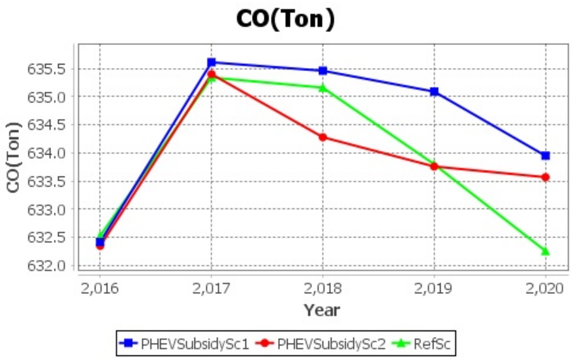
Charging Posts in 2020 (Zhuge et al., 2019d)

4.2.4 The Influence of PHEV Subsidy on the Urban Environment

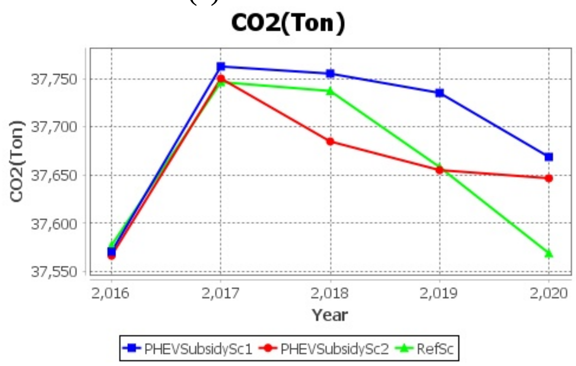
Doubling PHEV subsidy in either way can have different impacts on the total amounts of petrol consumed and vehicular emissions, as shown in Figure 5. In addition, adding more PHEVs in the tested scenarios could increase the amounts of petrol consumed and vehicular emissions in 2020, which is not generally expected. The unexpected result could be caused by many factors in such a dynamic and complex system, such as the changes in travel patterns of drivers, land use, residential locations of vehicle owners and layouts of transport infrastructures. More importantly, all of these factors interact with each other and evolve over time, which makes it rather difficult to exactly point out the reason. In addition, the differences between the RefSc and test scenarios in vehicular emissions and energy consumption are small (compared to the total amounts of emissions or energy consumed), suggesting that the unexpected result might be caused by some stochastic mechanisms in SelfSim-EV, though each SelfSim-EV scenario was run ten times and the average is used here. In order to further examine the influence of randomness on the model results, each scenario should be run for as many times (e.g., 100 times) as possible. However, the trade-off between computing time and model accuracy should be made, as running SelfSim-EV is computationally expensive.



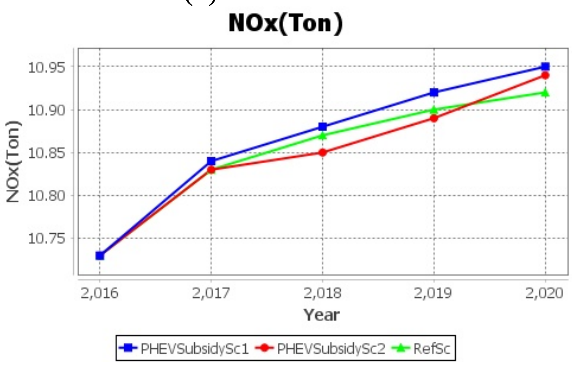
(a) HC Emission



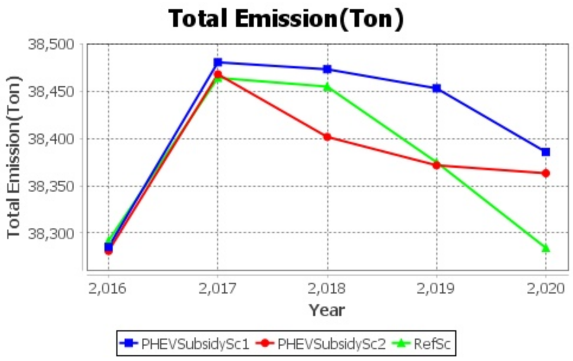
(b) CO Emission



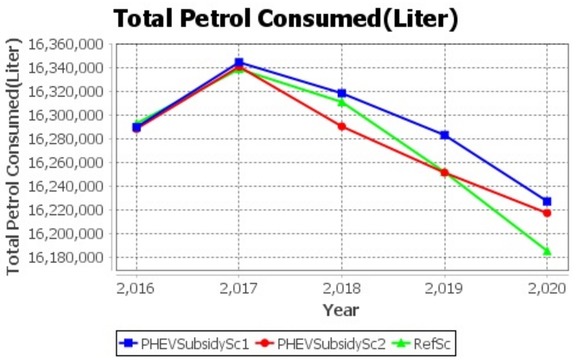
(c) CO_2 Emission



(d) NOx Emission



(e) Total Vehicular Emissions

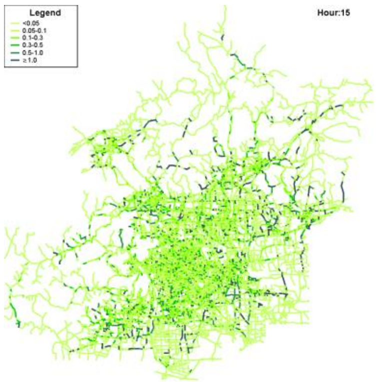


(f) Petrol Consumption

Figure 5 One-Day Vehicular Emissions and Petrol Consumption for the Period from 2016 to 2020 (Note: the RefSc is cited from (Zhuge et al., 2019d))

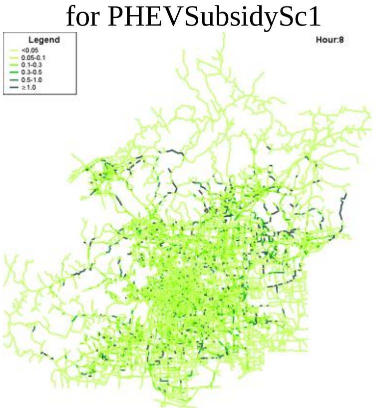
Further, the spatial analysis of the influence of PHEV subsidy on the environment is conducted: Figure 6 maps the spatial differences in the one-day link-based vehicular emissions between the "what-if" and RefSc scenarios, using a morning peak hour (7-8AM), an evening peak hour (6-7PM), and an off-peak hour (2-3PM) as examples. It can be found that doubling the PHEV subsidy in either way can heavily change the spatial distribution of link-based vehicular emissions at both peak and off-peak hours. Furthermore, the impact at the peak hours appears to be less significant than that at the off-peak hours. Also, the link-based emissions in the outer districts tend to be more heavily influenced by the PHEV subsidy than those in the central districts. This can also be found at the traffic zone level (see Figure A4 in Supplementary Material).

(a) Morning Peak Hour (8AM) for PHEVSubsidySc1

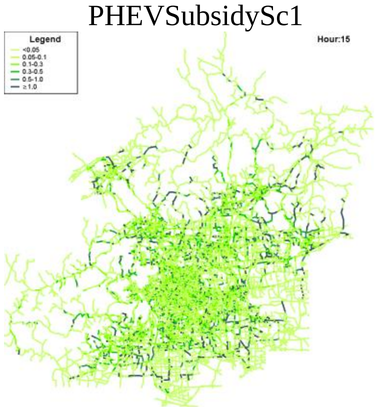


(b) Off-Peak Hour (3PM) for PHEVSubsidySc1

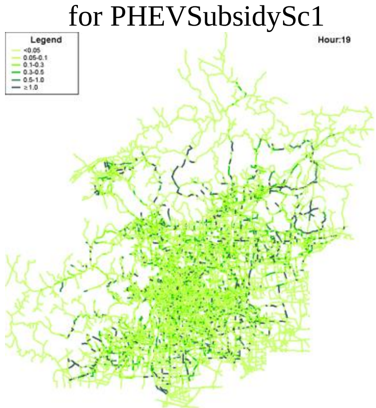
(c) Evening Peak Hour (7PM) for PHEVSubsidySc1



(d) Morning Peak Hour (8AM)



(e) Off-Peak Hour (3PM) for



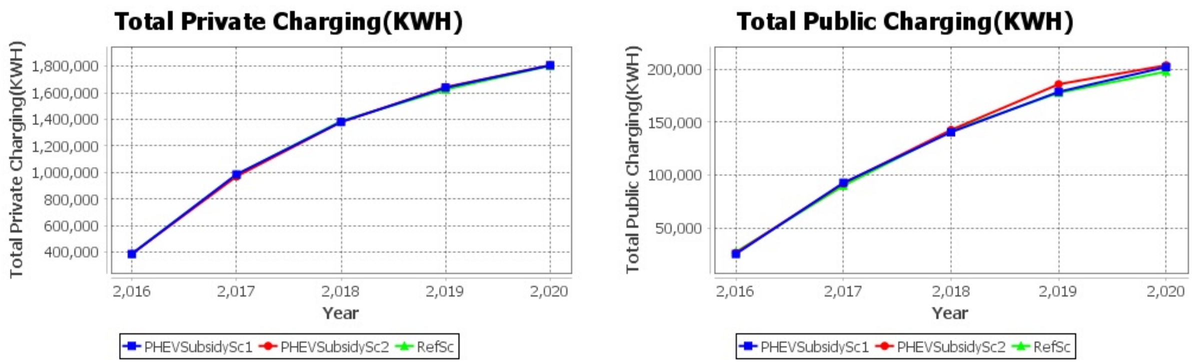
(f) Evening Peak Hour (7PM)

for PHEVSubsidySc2 PHEVSubsidySc2 for PHEVSubsidySc2

Figure 6 Spatial differences in the One-Day Link-based Vehicular Emissions between the “What-If” and RefSc Scenarios in 2020 (Zhuge et al., 2019d)

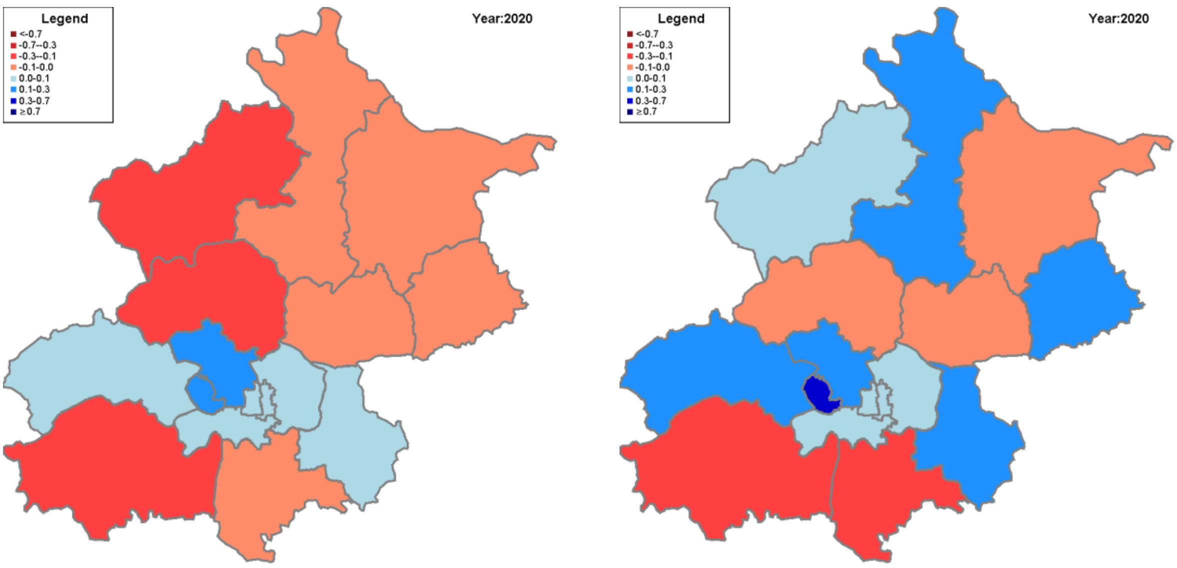
4.2.5 The Influence of PHEV Subsidy on the Power Grid System

As shown by Figure 7, the “what-if” scenarios do not significantly differ from RefSc in the total amount of electricity provided by charging posts in one particular weekday, though a marginal increase in public charging demand can be found after 2018 (see Figure 7-(b)) when the number of PHEV purchasers start increasing (see Figure 2-(c)). This indicates that doubling PHEV subsidy in either way does increase the number of PHEV purchasers, but the extra added PHEV owners appear not to consume too much electricity, probably due to the relatively small electric driving range of PHEV. However, the changes in PHEV subsidy do significantly influence the spatial distribution of actual charging demand through charging posts at both zone- and district- levels (see Figure A6 in Supplementary Material and Figure 8 below, respectively). Take the district-level differences in public charging demand for example (see Figure 8), the demands in all of the districts are to some extent influenced by the changes in PHEV subsidy. Furthermore, the outer districts tend to be more heavily influenced by the changes than the central districts (especially the Dongcheng, Xicheng, Chaoyang and Fengtai districts). The heavy influence on the spatial distribution of charging demand could be attributed to many factors, such as the slight increase in the public charging demand after 2018 (Figure 7-(b)) and the significant changes in the layout of public charging posts (see Figure 4). These spatially explicit results about the influences of PHEV subsides would be particularly useful for decision-makings of relevant stakeholders, such as local authorities. Given the potential influences on the power grid system, the policy makers can decide whether or not to double PHEV subsidies; If yes, they also need to think how to deal with the spatial changes in charging demand, for example, through policies and infrastructure optimization.



(a) Private Charging (b) Public Charging

Figure 7 One-Day Electricity Consumption through Charging Posts for the Period from 2016 to 2020 (Note: the RefSc is cited from (Zhuge et al., 2019d))



(a) Difference between PHEVSubsidySc1 and RefSc

(b) Difference between PHEVSubsidySc2 and RefSc

Figure 8 District-Level Differences between "What-If" and RefSc Scenarios in Public Charging Demand in 2020 (Zhuge et al., 2019d)

4.3 Scenario B - Petrol Prices

4.3.1 Description of Scenario B

EV has an obvious advantage over CV in terms of price per kilometre of travel. For example, BEV drivers in Beijing can save around 30RMB when they travel 100 kilometres, compared with CV drivers. The scenarios here will investigate the influence of the petrol price on the EV uptake. As shown by Figure 9, the petrol prices in Beijing, including the prices for 90# Petrol, 93# Petrol and 97# Petrol (which differ from each other in octane values), have varied heavily over the past few years, ranging from around 5.5 to 8.5 RMB/ Litre. The average price of the three petrol types has been used as the petrol price in the simulation from 2010 to 2017. The RefSc scenario also assumed that the petrol price would level off at 6.5 RMB/ Litre during the period from 2018 to 2020. The "what-if" scenarios here attempt to quantify the extent to which the petrol price may influence the EV uptake in Beijing. Specifically, according to the historical petrol prices from 2009 to 2017, three scenarios with different petrol prices ranging from 5.5 to 8.5 RMB/ Litre are set up as follows:

- **Scenario B1 (Petro55S1):** the petrol price is set to 5.5 RMB/ Litre;
- **Scenario B2 (Petro75S2):** the petrol price is set to 7.5 RMB/ Litre;
- **Scenario B3 (Petro85S3):** the petrol price is set to 8.5 RMB/ Litre.

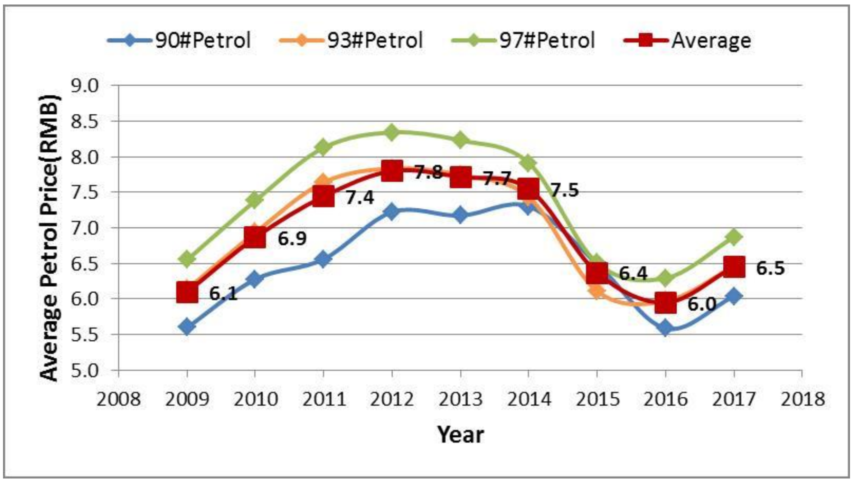
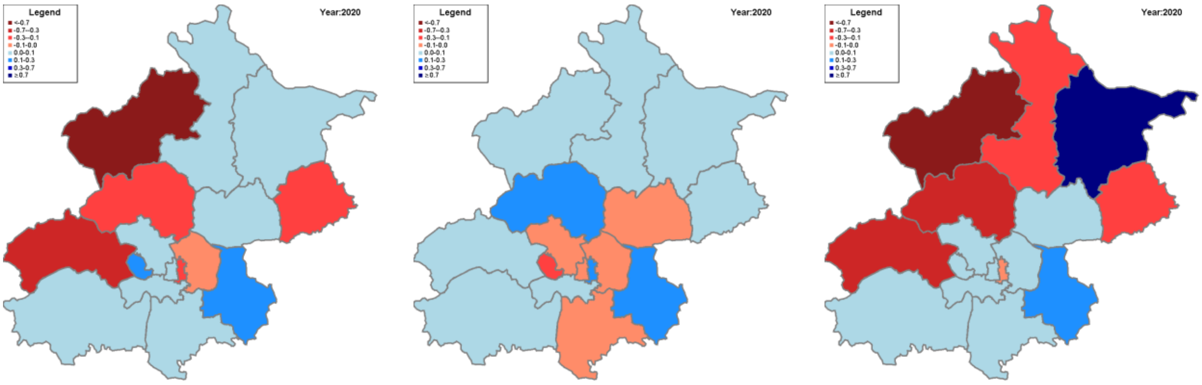


Figure 9 Petrol Prices in Beijing from 2009 to 2017 (Data Source: http://data.eastmoney.com/OilPrice/oil_city.aspx?city=beijing)

4.3.2 The Influence of Petrol Price on the EV Market and its Connected Urban Elements

(1) Influence on the EV Market: Statistical and Spatial Perspectives

The petrol price is found as a non-influential factor to the adoption of EVs at the macro level, as evident from the almost no changes in EV sales, prices or subsides (see Figure A7 in Supplementary Material). However, varying the petrol prices within the three "what-if" scenarios can heavily influence the spatial distributions of both CV and EV owners at the multiple resolutions (see Figure A8 in Supplementary Material), based on the analysis of their residential locations. Take PHEV owners as example (see Figure 10 below), the three different petrol prices could have completely different spatial influences on the PHEV adopters at the district level, in terms of their residential locations. In addition, the Petro75S2 scenario with the petrol price of 7.5 RMB/ Litre tends to have more significant influences in those central districts, compared to the other two scenarios, namely Petro55S1 (petrol price =5.5 RMB/ Litre) and Petro85S3 (petrol price =8.5 RMB/ Litre). These spatial differences could be caused by a wide variety of factors, such as the changes in travel patterns, residential locations of vehicle owners and land use patterns, as discussed before. For example, the change in petrol price could influence the travel utility of potential CV drivers and further the utility of purchasing a CV. As a result, the decision-making on vehicle purchase could be influenced, which could result in a completely different spatial distribution of vehicle owners.

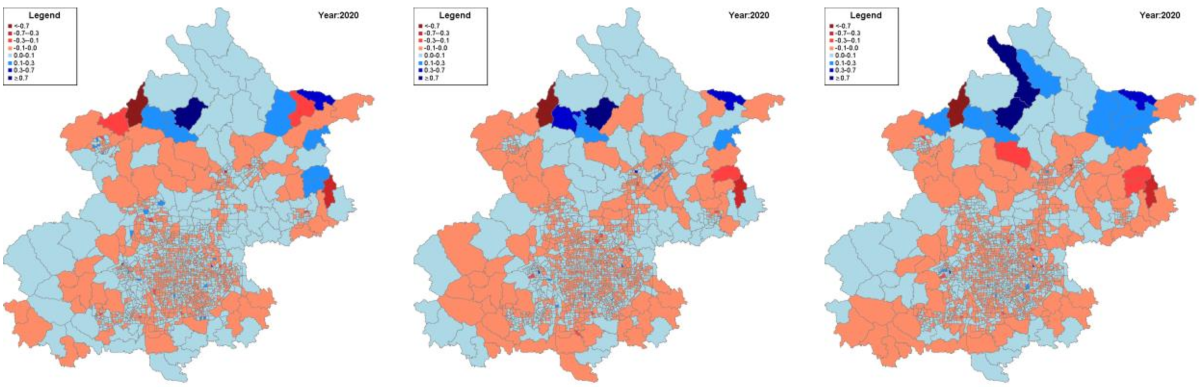


(a) PHEV Owners in Petrol55S1 (b) PHEV Owners in Petrol75S2 (c) PHEV Owners in Petrol85S3

Figure 10 Differences between "What-If" and RefSc Scenarios in the Residential Location of PHEV Owner in 2020 at the District Level (Zhuge et al., 2019d)

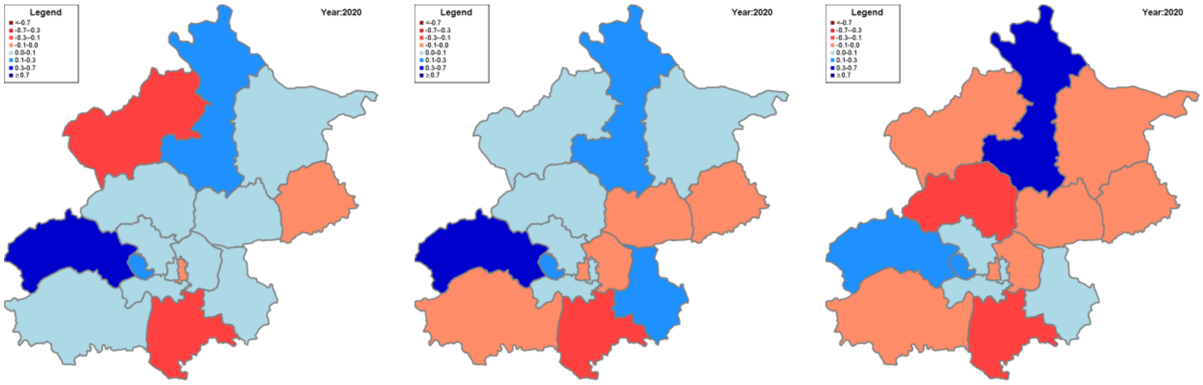
(2) Influences on the Environment, Power Grid System and Transport Infrastructures

At the aggregate level, since the influence of petrol price on the EV market tends to be slight, the further influences on the connected elements (including vehicular emissions, electricity consumption, and EV-related infrastructures) are marginal (see Figure A9, Figure A11 and Figure A13 in Supplementary Material, respectively). However, the changes in petrol price can to some extent influence the geographical distributions of vehicular emissions (see Figure 11), charging demand (e.g., public charging demand, see Figure 12) and EV-related facilities (e.g., public charging posts, see Figure 13). In particular, the outer districts or traffic zones tend to be more influenced by the changes. This consistency indicates that the impacts of EV adoption on the urban environment, electricity system and EV-related facilities appear to be associated with each other at the disaggregate level.



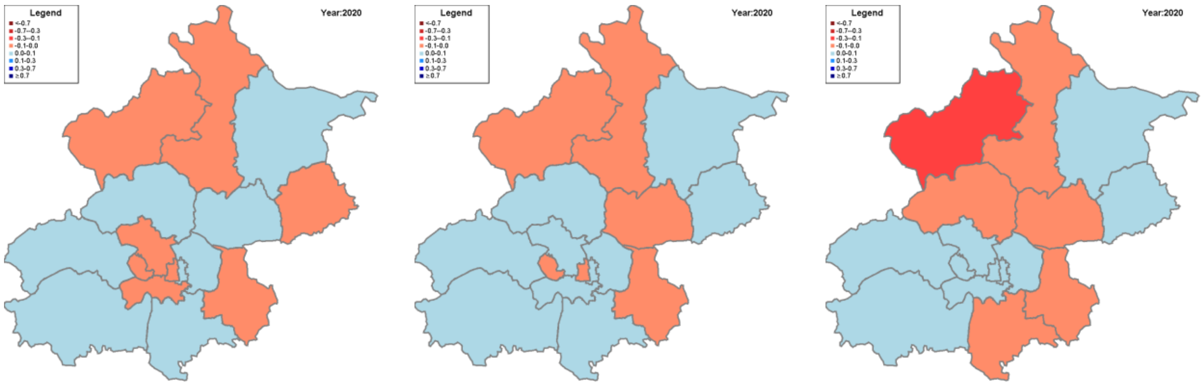
(a) Difference between Petrol55S1 and RefSc (b) Difference between Petrol75S2 and RefSc (c) Difference between Petrol85S3 and RefSc

Figure 11 Spatial differences between the "What-If" and RefSc Scenarios in the One-Day Zone-based Vehicular Emissions in 2020 (Zhuge et al., 2019d)



(a) Difference between Petrol55S1 and RefSc | (b) Difference between Petrol75S2 and RefSc | (c) Difference between Petrol85S3 and RefSc

Figure 12 District-Level Differences between "What-If" and RefSc Scenarios in Public Charging Demand in 2020 (Zhuge et al., 2019d)



(a) Difference between Petrol55S1 and RefSc | (b) Difference between Petrol75S2 and RefSc | (c) Difference between Petrol85S3 and RefSc

Figure 13 Differences between "What-If" and RefSc scenarios in the District-Level Layout of Public Charging Posts in 2020 (Zhuge et al., 2019d)

4.4 Scenario C - Electricity Price for EVs

4.4.1 Description of Scenario C

Since the electricity price for EVs through private charging is determined by the residential electricity tariff method and thus tends to level off over the period from 2016 to 2020, the scenarios here will only explore the impacts of the electricity price for EVs through public charging (that is the sum of the electricity and service fees) on the EV adoption. Furthermore, the Time-Of-Use (TOU) tariff setting method currently applied to the public electricity price for EVs is very likely to continue. Therefore, different TOU tariff setting methods will be explored within the scenarios. More specifically, the tariff setting method in 2016 (see Table 1) will be used as the reference, and the other scenarios will increase the electricity price by some specific percentages ranging from 30% to 100%. The three scenarios (namely Elec30S1, Elec70S2 and Elec100S3) with the increasing rates of 30%, 70% and 100%, respectively, are summarized in Table 2.

Table 1 Public Electricity Prices for EVs in 2016 in Beijing

Period	Time of Day	Electricity Fee (RMB/kW·h)	Service Fee (RMB/kW·h)	Total (RMB/kW·h)
Peak	**10:00-15:00**	1.0044	0.8	1.8044
	18:00-21:00			
Normal	**07:00-10:00**	0.695	0.8	1.495
	15:00-18:00			
	21:00-23:00			
Off-Peak	**23:00-07:00**	0.3946	0.8	1.1946

Table 2 Public Electricity Prices for EVs in the Scenarios (RMB/kW·h) (Zhuge et al., 2019d)

Period	Time of Day	Reference Scenario (RefSc)	Scenario C1 -30% (Elec30S1)	Scenario C2 -70% (Elec70S2)	Scenario C3 -100% (Elec100S3)
Peak	**10:00-15:00**	1.8044	2.3457	3.0675	3.6088
	18:00-21:00				
Normal	**07:00-10:00**	1.4950	1.9435	2.5415	2.9900
	15:00-18:00				
	21:00-23:00				
Off-Peak	**23:00-07:00**	1.1946	1.5530	2.0308	2.3892

4.4.2 The Influence of Electricity Price on the EV Market and its Connected Urban Elements

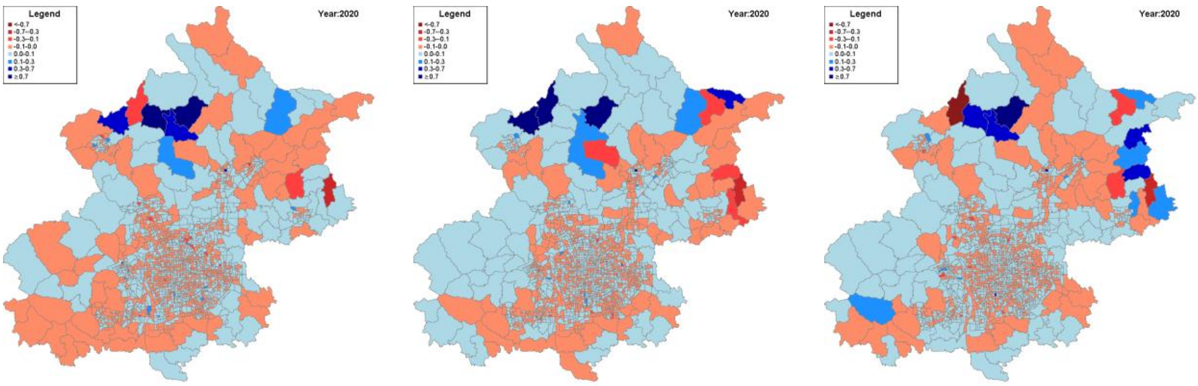
(1) Influence on the EV Market: Statistical and Spatial Perspectives

Similar to the petrol price (as discussed in Section 4.3.2), the electricity price for EV drivers appears to also have little influence of the uptake of EV at the macro level, as evident from the slight changes in vehicle sales, vehicle prices and EV subsidies from 2016 to 2020 (see Figure A14 in Supplementary Material). However, varying electricity price can somewhat influence the spatial distributions of CV and BEV owners, and have a significant influence on that of PHEV owners (see Figure A15 in Supplementary Material), based on the analysis of their residential locations. The spatial changes are likely attributed to the interactions among the EV-related urban systems, such as the typical interaction between transport and land use systems (Waddell, 2011). The reasons why the spatial change in PHEV owners tends to be much heavier is likely because of the relatively small number of PHEV owners.

(2) Influences on the Environment, Power Grid System and Transport Infrastructures

Due to the marginal changes in the ownerships of both CV and BEV, the further influences of electricity price on the urban environment, electricity system and EV-related facilities are marginal at the macro level (see Figure A16, Figure A17 and Figure A18 in Supplementary Material, respectively). However, the spatial changes in vehicle owners can somewhat influence the geographical distributions of vehicular emissions (see Figure 14 below), charging demand (see Figure 15 below) and transport facilities (e.g., public charging posts, see Figure 16 below). More specifically, for vehicular emissions, the outer districts tend to be more influenced by the change of electricity price (see Figure 14 below); Varying electricity price appears to have a more significant influence on the public charging demand (see Figure 15). One possible reason could be that the layout of public charging posts is heavily influenced (see Figure 16).

Based on both the aggregate and disaggregate analyses above, the EV stakeholders (e.g., fuel suppliers and local authorities) are suggested to bear in mind the spatial changes in vehicle emissions, transport infrastructures and charging demand when they shape their policies regarding prices, as the EV market expansion is connected to several urban sub-systems, such as land use, environment and energy systems.

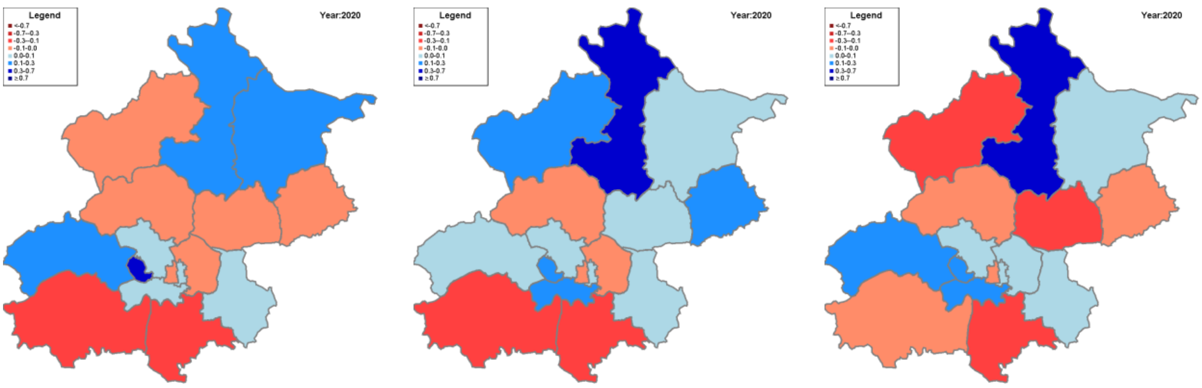


(a) Difference between Elec30S1 and RefSc

(b) Difference between Elec70S2 and RefSc

(c) Difference between Elec100S3 and RefSc

Figure 14 Spatial differences in the One-Day Zone-based Vehicular Emissions between the “What-If” and RefSc Scenarios in 2020 (Zhuge et al., 2019d)

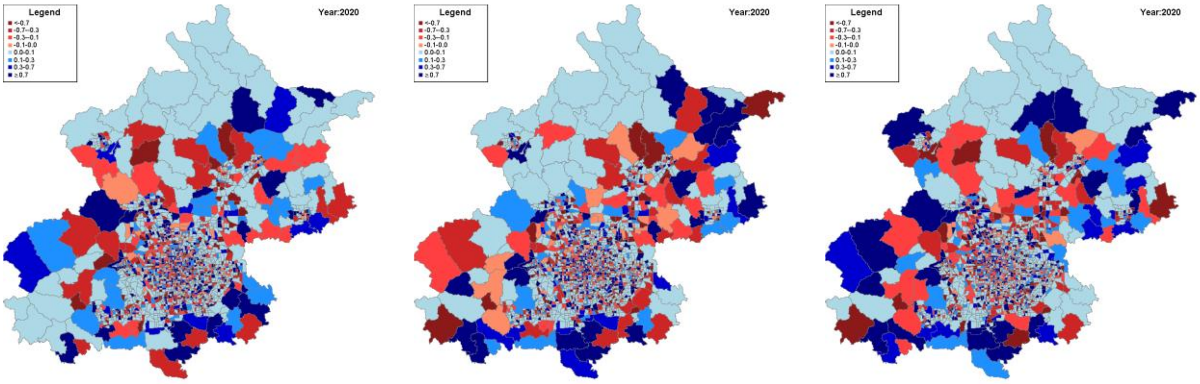


(a) Difference between Elec30S1 and RefSc

(b) Difference between Elec70S2 and RefSc

(c) Difference between Elec100S3 and RefSc

Figure 15 District-Level Differences between “What-If” and RefSc Scenarios in Public Charging Demand in 2020 (Zhuge et al., 2019d)



(a) Difference between Elec30S1 and RefSc

(b) Difference between Elec70S2 and RefSc

(c) Difference between Elec100S3 and RefSc

Figure 16 Differences between “What-If” and RefSc scenarios in the Zone-Level Layout of Public Charging Posts in 2020 (Zhuge et al., 2019d)

5 Policy Implications

Several “what-if” scenarios were set up to investigate how the three typical types of cost-related factors, namely PHEV subsidy, petrol price and electricity price, may influence the uptake of EVs and further the connected urban elements, including the urban environment, electricity system and EV-related facilities, compared to a Reference Scenario (RefSc) assuming that the urban system would evolve as before.

(1) Discussion on PHEV Subsidy

The two “what-if” scenarios (in Scenario A, see Section 4.2), which double the PHEV subsidy in two different ways, suggest that subsidies are an effective way to promote the purchase of PHEVs through the reduction of upfront cost, which has also been found in others’ studies (Hao et al., 2014; Lieven, 2015; Sierzchula et al., 2014; Wang et al., 2017). Furthermore, the increase in PHEV sale can influence the spatial distributions of BEV, PHEV and CV owners in an either direct or indirect way. Specifically, the spatial changes in PHEV and CV owners are likely influenced by the numbers of PHEV and CV directly; while the spatial change in BEV owners tend to be influenced in an indirect way, for example, through the interactions between vehicle purchasers in the dynamic vehicle market. The influence of PHEV subsidies on the uptake of EV can further impact those EV-related urban elements to some extent, especially at the disaggregate levels, as evident from the significant spatial differences between the “what-if” and RefSc scenarios in vehicular emissions, charging demand and charging posts at the multiple resolutions, ranging from the facility level to district level. Such spatially explicit results could be helpful for different EV-related stakeholders involved, such as the government, manufacturers, urban planners, fuel suppliers and utility companies (Zhuge et al., 2019d). For example, PHEV and CV currently share a specific number of vehicle purchase permits allocated by the Beijing government each year, according to the so-called license plate lottery policy (Yang et al., 2016), but PHEV is significantly less competitive to CV, due to its much higher sale price. The scenario analyses in this paper suggested increasing PHEV subsidies would be an effective way to reduce the upfront cost of PHEV and thus to encourage people to purchase. Therefore, the Beijing government is suggested to consider PHEV subsidy as a possible policy. Also, it should bear in mind that the possible further influences on the urban environment, electricity system and EV-related facilities when a higher PHEV subsidy is provided: 1) the global environmental impact tends to be marginal and thus the environmental benefits should not be generally expected through the increase of PHEV subsides; there is no significant increase in charging demand and thus higher PHEV subsidies should not put too much pressure on the electricity system; there is also no heavy change in the quantity of charging posts needed, but the layout of charging posts should be optimized, according to the changes in residential locations and individual travel patterns of EV owners. Although such systematic spatial analyses of EV subsidies are very useful, but have received scant attention in the previous studies of EV subsides (Breetz and Salon, 2018; Hao et al., 2014; Helveston et al., 2015; Zhuge and Shao, 2019).

(2) Discussion on Fuel Price

Both electricity and petrol prices appear to be non-influential to neither PHEV nor BEV sales. As a result, varying electricity and petrol prices could have little influence on those urban elements connected with the EV market at the macro level. However, some other studies suggested that the adoption of EV was related with fuel cost (Beresteanu and Li, 2011; Chandra et al., 2010; Diamond, 2009; Eppstein et al., 2011; Gallagher and Muehlegger, 2011), which differs from the finding in this paper. Specifically, (Beresteanu and Li, 2011) found that the EV sale in 2006 would be 37% lower given that the gasoline prices remained since 1999 in the USA; Again in the USA, (Diamond, 2009) found the correlation between gasoline prices and hybrid EV sale was much stronger than that between incentive policies and EV sale; The studies by (Eppstein et al., 2011), (Gallagher and Muehlegger, 2011) and (Chandra et al., 2010) found that the rise of gasoline prices could increase the penetration rate of EV. It would be rather difficult to point out the exact reason why the fuel price in our study is not influential in such a dynamic complex urban system. One possible reason may be that the upfront cost (or EV price) tends to much more influential than fuel cost to the uptake of EVs, as evident from a recent empirical finding about the influential factors in the Beijing EV market (Zhuge and Shao, 2019): it was found that vehicle price accounted for 32.3% of the importance, compared to the other five typical factors that have been widely studied, namely vehicle usage (28.1%), social influence (9.7%), environmental awareness (9.6%), purchase restriction (12.4%) and traffic restriction (7.8%). Although both electricity and petrol prices almost do not influence the EV adoption at the macro level, they can heavily influence the spatial distributions of vehicular emissions, the electricity demand from EVs and charging facilities. Therefore, varying the fuel price would still be helpful if the EV-related stakeholders want to change the geographical distributions of those connected urban elements, in order to meet their specific requirements. For example, local authorities may want to get an optimal distribution of charging demand from EVs through varying fuel price, in order to mitigate the potential negative impact on the electricity system. Such systematic spatial analyses of the influences of fuel price on the uptake of EV have been seldom carried out (Chandra et al., 2010; Eppstein et al., 2011; Gallagher and Muehlegger, 2011), though they can help better understand the role of fuel price at multiple resolutions.

6 Conclusions

This paper tried to explore the role of those cost-related factors (i.e., Plug-in Hybrid Electric Vehicle (PHEV) subsidies, electricity prices and petrol prices) in the uptake of Electric Vehicle (EV) at the individual level, using a calibrated and validated agent-based urban model (SelfSim-EV). The key findings are summarized as follows: Doubling PHEV subsides could increase the PHEV sale, which could slightly influence those connected urban elements at the macro level, such as the number of public charging posts. However, there was almost no influence of fuel prices on these urban elements. At the micro level, varying PHEV subsidy or fuel price could heavily influence these urban elements: these "what-if" scenarios had significantly different spatial distributions of vehicular emissions, electricity demand and charging posts, compared to the Reference Scenario (RefSc). Both the aggregate results (e.g., EV penetration rates, sale prices and subsidies) and spatially disaggregate outcomes (e.g., the geographical distribution of vehicular emissions at the link level and spatial distribution of charging demand at the zone level) are expected to be useful for the decision-makings of the EV-related stakeholders, such as the government, urban planners and fuel suppliers.

The future research work will be focused on the following three aspects: First, although SelfSim-EV was found as a quite useful tool to investigate the role of possible influential factors in the diffusion of EV, it was difficult to explain some unexpected results coming out from the interactions between several evolving urban sub-systems (e.g., transportation and land use systems). Further analyses are needed to provide insights into the interactions at the individual level, so as to better understand those unexpected results; Second, fuel prices were found as not influential to the uptake of EVs in this case study. However, this may vary from case to case, and thus should be further investigated in as many case studies as possible; Third, this paper is focused on two typical types of cost-related factors, namely subsidy and fuel price. It would be interesting to further explore how other policies (e.g., the license plate lottery policy) may influence the uptake of EVs using SelfSim-EV. This would help policy makers to choose those policies that could promote the development of EVs more effectively.

Acknowledgement

This research was supported by the National Natural Science Foundation of China (Grant No. 51678044), the Fundamental Research Funds for the Central Universities (NO. 2017JBZ106), China, the Hong Kong Polytechnic University [1-BE2J], and the ERC Starting Grant #678799 for the SILCI project (Social Influence and disruptive Low Carbon Innovation). We would also thank Dr. Mike Bithell for discussing with us about the development and application of the SelfSim-EV model.

References

Bakker, S. and Trip, J.J., 2013. Policy options to support the adoption of electric vehicles in the urban environment. Transportation Research Part D: Transport and Environment, 25: 18-23.

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

Biresselioglu, M.E., Kaplan, M.D. and Yilmaz, B.K., 2018. Electric mobility in Europe: A comprehensive review of motivators and barriers in decision making processes. Transportation Research Part A: Policy and Practice, 109: 1-13.

Bjerkan, K.Y., Nørbech, T.E. and Nordtømme, M.E., 2016. Incentives for promoting battery electric vehicle (BEV) adoption in Norway. Transportation Research Part D: Transport and Environment, 43: 169-180.

Breetz, H.L. and Salon, D., 2018. Do electric vehicles need subsidies? Ownership costs for conventional, hybrid, and electric vehicles in 14 US cities. Energy Policy, 120: 238-249.

Buekers, J., Van Holderbeke, M., Bierkens, J. and Int Panis, L., 2014. Health and environmental benefits related to electric vehicle introduction in EU countries. Transportation Research Part D: Transport and Environment, 33: 26-38.

Bunsen, T., Cazzola, P., Gorner, M., Paoli, L., Scheffer, S., Schuitmaker, R., Tattini, J. and Teter, J., 2018. Global EV Outlook 2018: Towards cross-modal electrification. Retrieved on 19th May 2019, from http://centrodeinnovacion.uc.cl/assets/uploads/2018/12/global_ev_outlook_2018.pdf.

Campello-Vicente, H., Peral-Orts, R., Campillo-Davo, N. and Velasco-Sanchez, E., 2017. The effect of electric vehicles on urban noise maps. Applied Acoustics, 116: 59-64.

Casals, L.C., Martinez-Laserna, E., García, B.A. and Nieto, N., 2016. Sustainability analysis of the electric vehicle use in Europe for CO2 emissions reduction. Journal of Cleaner Production, 127: 425-437.

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

Coad, A., de Haan, P. and Woersdorfer, J.S., 2009. Consumer support for environmental policies: An application to purchases of green cars. Ecological Economics, 68(7): 2078-2086.

Diamond, D., 2009. The impact of government incentives for hybrid-electric vehicles: Evidence from US states. Energy Policy, 37(3): 972-983.

Eppstein, M.J., Grover, D.K., Marshall, J.S. and Rizzo, D.M., 2011. An agent-based model to study market penetration of plug-in hybrid electric vehicles. Energy Policy, 39(6): 3789-3802.

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

Hao, H., Ou, X., Du, J., Wang, H. and Ouyang, M., 2014. China's electric vehicle subsidy scheme: Rationale and impacts. Energy Policy, 73: 722-732.

Hao, H., Wang, H. and Ouyang, M., 2011. Fuel conservation and GHG (Greenhouse gas) emissions mitigation scenarios for China’s passenger vehicle fleet. Energy, 36(11): 6520-6528.

Hardman, S., Chandan, A., Tal, G. and Turrentine, T., 2017. The effectiveness of financial purchase incentives for battery electric vehicles–A review of the evidence. Renewable and Sustainable Energy Reviews, 80: 1100-1111.

Helveston, J.P., Liu, Y., Feit, E.M., Fuchs, E., Klampfl, E. and Michalek, J.J., 2015. Will subsidies drive electric vehicle adoption? Measuring consumer preferences in the US and China. Transportation Research Part A: Policy and Practice, 73: 96-112.

Horni, A., Nagel, K. and Axhausen, K.W., 2016. The Multi-Agent Transport Simulation MATSim. Ubiquity, London.

IEA, 2018. Nordic EV Outlook 2018 - Insights from leaders in electric mobility. Retrieved on 1st September 2019 from https://webstore.iea.org/nordic-ev-outlook-2018.

Lévay, P.Z., Drossinos, Y. and Thiel, C., 2017. The effect of fiscal incentives on market penetration of electric vehicles: A pairwise comparison of total cost of ownership. Energy Policy, 105: 524-533.

Langbroek, J.H., Franklin, J.P. and Susilo, Y.O., 2016. The effect of policy incentives on electric vehicle adoption. Energy Policy, 94: 94-103.

Li, W., Long, R., Chen, H. and Geng, J., 2017. A review of factors influencing consumer intentions to adopt battery electric vehicles. Renewable and Sustainable Energy Reviews, 78: 318-328.

Lieven, T., 2015. Policy measures to promote electric mobility–A global perspective. Transportation Research Part A: Policy and Practice, 82: 78-93.

Mersky, A.C., Sprei, F., Samaras, C. and Qian, Z.S., 2016. Effectiveness of incentives on electric vehicle adoption in Norway. Transportation Research Part D: Transport and Environment, 46: 56-68.

Noori, M. and Tatari, O., 2016. Development of an agent-based model for regional market penetration projections of electric vehicles in the United States. Energy, 96: 215-230.

Rai, V. and Henry, A.D., 2016. Agent-based modelling of consumer energy choices. Nature Climate Change, 6(6): 556.

Sepehri, A. and Sarrafzadeh, M.-H., 2018. Effect of nitrifiers community on fouling mitigation and nitrification efficiency in a membrane bioreactor. Chemical Engineering and Processing - Process Intensification, 128: 10-18.

Sierzchula, W., Bakker, S., Maat, K. and Van Wee, B., 2014. The influence of financial incentives and other socio-economic factors on electric vehicle adoption. Energy Policy, 68: 183-194.

Waddell, P., 2011. Integrated land use and transportation planning and modelling: addressing challenges in research and practice. Transport Reviews, 31(2): 209-229.

Wang, S., Li, J. and Zhao, D., 2017. The impact of policy measures on consumer intention to adopt electric vehicles: Evidence from China. Transportation Research Part A: Policy and Practice, 105: 14-26.

Yang, J., Liu, A., Qin, P. and Linn, J., 2016. The effect of owning a car on travel behavior: Evidence from the Beijing license plate lottery. Retrieved on 24th September 2018 from http://www.rff.org/files/document/file/RFF-DP-16-18.pdf.

Zhang, K. and Batterman, S., 2013. Air pollution and health risks due to vehicle traffic. Science of the Total Environment, 450: 307-316.

Zhuge, C. and Shao, C., 2018a. Agent-based modelling of locating public transport facilities for conventional and electric vehicles. Networks and Spatial Economics, 18(4): 875-908.

Zhuge, C. and Shao, C., 2018b. Agent-based modelling of purchasing, renting and investing behaviour in dynamic housing markets. Journal of Computational Science, 27: 130-146.

Zhuge, C. and Shao, C., 2019. Investigating the factors influencing the uptake of electric vehicles in Beijing, China: Statistical and spatial perspectives. Journal of Cleaner Production, 213: 199-216.

Zhuge, C., Shao, C., Gao, J., Dong, C. and Zhang, H., 2016. Agent-based joint model of residential location choice and real estate price for land use and transport model. Computers, Environment and Urban Systems, 57: 93-105.

Zhuge, C., Shao, C. and Li, X., 2019a. A comparative study of en route refuelling behaviours of conventional and electric vehicles in Beijing, China. Sustainability, 11(14): 3869.

Zhuge, C., Shao, C. and Li, X., 2019b. Empirical analysis of parking behaviour of conventional and electric vehicles for parking modelling: A case study of Beijing, China. Energies, 12(16): 3073.

Zhuge, C., Shao, C., Wang, S. and Hu, Y., 2018a. An agent- and GIS-based virtual city creator: A case study of Beijing, China. Journal of Transport and Land Use, 11(1): 1231-1256.

Zhuge, C., Shao, C. and Wei, B., 2018b. An agent-based spatial urban social network generator: A case study of Beijing, China. Journal of Computational Science, 29: 46-58.

Zhuge, C., Shao, C. and Yang, X., 2019c. Agent- and Activity- based Large-Scale Simulation of Enroute Travel, Enroute Refuelling and Parking Behaviours in Beijing, China. Journal of Computational Science.

Zhuge, C., Wei, B., Dong, C., Shao, C. and Shan, Y., 2019d. Exploring the future electric vehicle market and its impacts with an agent-based spatial integrated framework: A case study of Beijing, China. Journal of Cleaner Production, 221: 710-737.