Energy Policy 139 (2020) 111328

Contents lists available at ScienceDirect

Energy Policy

journal homepage: http://www.elsevier.com/locate/enpol

The role of the license plate lottery policy in the adoption of Electric Vehicles: A case study of Beijing

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ARTICLE INFO

Keywords:
License plate lottery policy
Electric vehicle
Market penetration
Agent-based modelling
Spatial analysis
SelfSim

ABSTRACT

Policy is an influential factor to the purchase and usage of Electric Vehicles (EVs). This paper is focused on the license plate lottery policy, a typical vehicle purchase restriction in Beijing, China. An agent-based spatial integrated urban model, SelfSim-EV, is employed to investigate how the policy may influence the uptake of EVs over time at the individual level. Two types of "what-if" scenario were set up to explore how the methods to allocate the vehicle purchase permits and the number of permits might influence the EV market expansion from 2016 to 2020. The results suggested that 1) both the allocation methods and the number of purchase permits could heavily influence the uptake of EVs and further its impacts on vehicular emissions, energy consumption and urban infrastructures; 2) compared to the baseline, both scenarios got significantly different spatial distributions of vehicle owners, transport facilities, vehicular emissions and charging demand at the multiple resolutions; 3) SelfSim-EV was found as a useful tool to quantify the nonlinear relationships between the increase of EV purchasers and the demand for transport facilities and electricity, and also to capture some unexpected results coming out from the interactions in the complex dynamic urban system.

1. Introduction

Replacing Conventional Vehicles (CVs) with Electric Vehicles (EVs) through the initiatives of urban transportation electrification is increasingly recognized as a prominent approach in the transport sector to mitigating the pressing challenges of climate change, energy scarcity and urban air quality (Chen et al., 2018; Zhuge and Shao, 2018a, 2019). The electrification of transport could be driven by many factors, and policy appears to one of the most important factors associated with the diffusion of EVs.

A variety of policies have been designed to promote the development of EVs from both the supply and demand sides: the supply-related policies generally target at EV-related stakeholders (Ma et al., 2017), such as vehicle manufacturers (Green et al., 2014; Gu et al., 2017; Jang et al., 2018) and energy suppliers (Jang et al., 2018; Melton et al., 2017); while the demand-related policies are generally focused on the EV consumers, aimed at promoting the purchase and usage of EVs by providing them with extra benefits that could be either financial or non-financial (e.g., subsidies and access to bus lane) (Zhuge and Shao, 2019). This paper will be focused on a demand-related and non-financial policy, namely license plate lottery policy, which is a typical vehicle purchase restriction.

The license plate lottery policy specifies a fixed number of vehicle purchase permits each year (or each month) and allocates them among applicants, who plan to purchase vehicles, at random or with a specific rule (Liu et al., 2018b; Zhuge and Shao, 2019). In order to promote the purchase and usage of EVs, some governments, such as the Beijing government, have split the number of vehicle purchase permits into two parts, which are for CV and EV applicants, respectively (Zhuge and Shao, 2019). The Beijing government tends to favour Battery Electric Vehicle

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https://doi.org/10.1016/j.enpol.2020.111328
Received 6 March 2019; Received in revised form 6 December 2019; Accepted 3 February 2020
Available online 24 February 2020

(BEV) over Plug-in Hybrid Electric Vehicle (PHEV) and only allocates dedicated purchase permits to BEV purchasers, excluding PHEV purchasers. As a result, PHEV and CV purchasers need to compete for a specific number of the so-called CV purchase permits. However, in theory, PHEV is one typical EV type, which is commonly accepted across the global. Therefore, this paper treats PHEV as one type of EV, rather than CV, though CV and PHEV share a fixed number of purchase permits. The lottery policy has been found as influential to vehicle ownerships, but it remains unclear how it may influence the uptake of EVs and further those EV-related urban elements over time and across space, including the urban environment (e.g., vehicular emissions), energy system (e.g., electricity consumption) and transport infrastructures (e.g., charging posts).

To fill this research gap, this paper attempts to assess the potential implications of the license plate lottery policy on both the diffusion of EV and its associated urban systems at the micro scale, using an agent-based spatial integrated microsimulation approach, SelfSim-EV (Zhuge et al., 2019d). SelfSim-EV is an EV version of SelfSim, which is an agent-based land use and transport model (Zhuge et al., 2016). The outcomes should be helpful 1) for local authorities to evaluate and optimize the lottery policy, 2) for vehicle manufacturers to make a profitable production plan, 3) for energy suppliers to respond wisely to the possible changes in the refuelling and charging demands 4) and for urban planners to locate and optimize transport infrastructures for both CVs and EVs.

2. Literature review

2.1. Policies for Electric Vehicles (EVs)

Financial incentives, which essentially try to reduce the cost of purchasing and using EVs, tend to be one of the most-used EV policies (Zhuge et al., 2019e), including subsides for EV purchase (Hardman et al., 2017; Jenn et al., 2018; Mirhedayatian and Yan, 2018; Wang et al., 2018) and tax exemptions for both EV purchase and use (Jenn et al., 2018; Ma et al., 2017; Wang et al., 2017b). Incentives could take many different forms (e.g., sale tax waivers and income tax credits) which are closely associated with the effectiveness of policy. For example, it was found that the type of tax incentive offered could be as important as the amount of the incentive (Gallagher and Muehlegger, 2011). In general, financial incentives have positive impacts on the uptake of EVs (Breetz and Salon, 2018; Fearnley et al., 2015; Liu and Xiao, 2018), because such incentives could make EVs price competitive (Figenbaum, 2017). For example, it was estimated that the Energy Policy Act of 2005 could increase EV sale by 0.0046% per dollar (Jenn et al., 2013); a similar finding in the USA suggested that on average, every 1000 dollar could increase EV sale by 2.6% (Jenn et al., 2018). However, the incentives could only become effective when they were sufficiently large, as evident from Jenn et al. (2013)'s empirical finding, which suggested the amount of subsidies should be above 1000 dollar in the USA. In some cases, the incentives could even not be effective to the uptake of EVs (Rudolph, 2016).

Financial incentive could be a very effective policy that could make EVs price competitive in a relatively short time, especially in terms of vehicle price, but in general, the amount of subsidies would decrease over time as the number of EV adopters increases. Therefore, some other strategies should be used as alternatives (Hao et al., 2014; Wang et al., 2017a). Increasing the benefits of using EVs instead of CVs (Ma et al., 2017), which could increase the attractiveness of EVs, has been found as promising alternatives (Langbroek et al., 2016a, 2016b). These include free parking (Langbroek et al., 2016a, 2016b; Wolbertus et al., 2018), the reduction in refuelling/charging costs (Rudolph, 2016; Shafiei et al., 2018; Wang et al., 2017b), access to specific lanes (e.g., bus lane and HOV lane) (Jenn et al., 2018; Langbroek et al., 2016b; Melton et al., 2017; Mersky et al., 2016), toll road exemptions (Bjerkan et al., 2016; Fearnley et al., 2015; Mersky et al., 2016). For example, the HOV lane was identified as a significant factor to the adoption of EVs, with an increase of 4.7% (Jenn et al., 2018). However, in some cases, these alternative policies might not be effective. For example, neither tool road exemptions nor bus lane access had a statistically significant relationship with BEV sales in Norway (Mersky et al., 2016). Also, free parking was found not significantly influential in China, based on a web-based survey with 247 samples (Wang et al., 2017b). Furthermore, educating consumers and providing them with information on EVs were found as important in the adoption of EVs in some cases (Hardman et al., 2017; Larson et al., 2014), as EVs were still quite new to many potential vehicle purchasers.

Since several policies, such as financial incentives, need to invest money, cost-benefit analyses have been conducted to analyse their benefits and costs (DeShazo et al., 2017; Fearnley et al., 2015; Yan, 2018). For example, Fearnley et al. (2015) found that several policies, including subsides and fiscal exemption, in German had a negative benefit-cost balance. Similarly, Yan (2018) found that it could be costly to reduce CO2 emissions through tax incentives. In addition, the policy implications to the uptake of EVs may vary across space, therefore several comparative studies have been carried out at city- and country-levels (Breetz and Salon, 2018; Melton et al., 2017; Zhang and Bai, 2017).

Most of the studies above have been only focused on the implications of different policies on the adoption of EVs. Some attempts have been made to further assess the implications of the policies on the associated urban elements, such as the environment (Melton et al., 2017; Pu et al., 2015; Yan, 2018) and energy systems (Liu, 2012). For example, it was found that the diffusion of EVs could significantly reduce both GHG emissions and energy demand in the road transport sector, but might have a negative impact at the national level (Liu, 2012). However, these studies have tended to pay little attention to the interactions between the EV market and those associated urban systems, such as transport, energy and environment systems. Specifically, in a complex and dynamic urban system, an EV-related policy might not only influence the purchase and usage of EVs, but also those urban elements associated with EVs, such as EV-related transport facilities (e.g., charging post) and urban environment (e.g., vehicular emissions) (Zhuge et al., 2019d). Therefore, an EV policy should be assessed in a more comprehensive and systematic way, so as to fully understand its potential implications. Such assessment outcomes would be more helpful for different stakeholders involved (e.g., urban/transport planners), as discussed before.

2.2. Methods and models for assessing the implications of EV policies

Agent-based model (McCoy and Lyons, 2014; Shafiei et al., 2012; Tran, 2012), system dynamics model (Ardilaa and Francob, 2013; Linder, 2011) and discrete choice model (He et al., 2014; Lee et al., 2012; Nemry and Brons, 2010) have been widely used to investigate the uptake of EV (Zhuge and Shao, 2019). Therefore, these three models, in theory, could also be used to evaluate the effectiveness of a policy to the diffusion of EV. Some attempts have been made to use system dynamics model (Fearnley et al., 2015; Liu and Xiao, 2018; Shafiei et al., 2018) and discrete choice model (including mixed logit model (Langbroek et al., 2016a; Rudolph, 2016; Wang et al., 2017b), binary logit model (Zhang et al., 2018) and multinomial logit model (Kwon et al., 2018)). However, agent-based model (Silvia and Krause, 2016), which is a typical approach to simulating complex urban systems, has received significantly less attention in the evaluation of an EV policy. While regression models (Jenn et al., 2018; Wang et al., 2017a; Wolbertus et al., 2018; Yan, 2018) tend to be one of the most-used approaches to evaluating such EV-related policies. Other methods also include probabilistic model (DeShazo et al., 2017), multivariate co-integration model (Ma et al., 2017) and multi-Level Perspective (MLP) transition theory (Figenbaum, 2017).

Compared with system dynamics model, discrete choice model and regression model, agent-based models have several advantages in evaluating the effectiveness of an EV policy (Heppenstall et al., 2011; Zhuge et al., 2018a, 2018b): 1) agent-based modelling can be easily coupled with spatial modelling. Therefore, the resulting model can assess the policy implications from a spatial perspective; 2) Heterogeneity. Individuals may respond differently to the same policy according to their own preferences and attributes (e.g. income and gender). Agent-based model is capable of simulating various heterogeneous behaviours, including purchase, travel and charging behaviours of EV. Therefore, agent-based modelling will be used in this paper to explore the role of the license plate lottery policy in the diffusion of EV.

2.3. License plate lottery policy

There are two typical vehicle purchase restrictions, namely license plate lottery and auction, which appear to be more widely used in Chinese cities, including Beijing, Shanghai and Guangzhou (Lai et al., 2018; Wang and Zhao, 2017; Zhang et al., 2018). Both of them are expected to be useful for vehicle ownership control, so as to mitigate traffic congestion, improve local air quality and reduce GHG emissions. Some of the studies have tried to investigate people's perception towards these two restrictions at the individual level, for example, using discrete choice models (Lai et al., 2018; Wang and Zhao, 2017).

The review here will be focused on the license plate lottery policy, which could have several different implications on the urban system: 1) Impacts on Daily Travel: it was found that the lottery policy might have little influence on travel time or distance, but did influence travel mode (Yang et al., 2016); Furthermore, it appeared that the lottery policy could also somehow improved the traffic system in Beijing, as evident from the increase of average driving speed from 22.6 km/h in 2010 to 25.3 km/h in 2011 (Yang et al., 2014); 2) Impacts on the Environment and Energy Systems. The work of Yang et al. (2014) suggested that the total number of vehicles in Beijing would decrease by 11% in 2020 because of the lottery policy, but the amount of fuel consumption would only decrease by 1%. In another study by Li and Jones (2015), it was found that the policy could reduce CO2 emissions from 23.90 to 15.55 million tons in 2020 in Beijing, given that the current policy continued; 3) Unexpected Impacts. It was found that the lottery policy could have a negative net impact on female employment rates (Liu et al., 2017) and also could reduce the number of births in a household (Liu et al., 2018a).

In order to promote the purchase of EVs at the same time, some lottery policies tried to allocate a specific number of purchase permits particularly to the potential EV purchasers, for example, in Beijing. As a result, EV purchasers could have much higher winning probability. Some attempts have been made to investigate the influence of license plate lottery policy on the adoption of EVs. For example, the work by (Zhang et al., 2018) found that the lottery policy could be more influential than EV subsides to the adoption of EVs in Beijing. However, these studies tended to pay almost no attention to the further influence of the EV adoption on the associated urban elements, such as the urban environment, energy system and transport infrastructures, resulting in an inadequate assessment with limited useful information obtained for those EV-related stakeholders (e.g., the government). On the other hand, those unexpected implications of the lottery policy on female labour supply and birth rates suggest that an integrated approach is needed in order to fully understand the policy implications, so as to capture some unexpected results coming out form the interactions between the EV diffusion and those associated urban systems (e.g., population system).

2.4. Research gaps

As reviewed in Section 2.1, a variety of policies either monetary or non-monetary have been issued to promote the purchase and usage of EVs across the global. Some of them have been found as influential to the uptake of EVs and could further benefit the environment and energy systems. However, these studies have tended to only assess the implication of the EV policies (including the license plate lottery policy) on the market penetration, paying significantly less attention to the potential further influences on those associated urban elements, such as the urban environment (e.g., vehicular emissions), energy system (e.g., energy consumption) and transport infrastructures (e.g., parking and charging facilities). In response, this paper attempts to assess policy implications in a more comprehensive and systematic way, considering both the diffusion of EVs and its associated urban elements.

As reviewed in Section 2.3, the license plate lottery policy, which is a typical vehicle purchase restriction, will be used as a specific example in this paper, as the role of the lottery policy in the diffusion of EVs still remains unclear. In addition, the lottery policy could also have some unexpected implications on those associated urban elements, such as population system (e.g., labour supply and birth rates). Therefore, an integrated approach, which can consider both the EV diffusion and its associated urban elements, would be useful for fully understanding the policy implications.

As reviewed in Section 2.2, system dynamics model, discrete choice model and regression model have been widely used to assess the implications of various EV-related policies. However, this paper will use agent-based modelling, which is a common approach to simulating the adoption of EV, but has received significantly less attention in evaluating the EV policies. Specifically, this paper will use an agent-based spatial integrated simulation model, SelfSim-EV (Zhuge et al., 2019d). The reasons are twofold: 1) SelfSim-EV was developed particularly for investigating the diffusion and impacts of EV diffusion (Zhuge et al., 2019d), and thus can be straightforwardly used here to assess the implications of the license plate lottery policy on the uptake of EV and further its associated elements; 2) SelfSim-EV is spatially explicit, meaning that the policy can be evaluated from a spatial perspective.

In summary, this paper attempts to explore the role of the license plate lottery policy in the diffusion of EV with an agent-based spatial integrated simulation model, SelfSim-EV, considering both the EV market penetration and its further influences on those associated elements (e.g., urban infrastructures). It is expected that the evaluation could help to fully understand the influence of the lottery policy on the diffusion of EVs over time and across space.

3. Methodology

3.1. An agent-based integrated urban model for Electric Vehicles (EVs): SelfSim- EV

As aforementioned, SelfSim-EV will be used here as a tool to explore the role of license plate lottery policy in the adoption of EV. The model was introduced in detail in our previous work of (Zhuge et al., 2019d), presenting its ability to investigate the diffusion and impacts of EVs. Therefore, the following introduction to SelfSim-EV will be focused on the interactions among its sub-models, as well as model dynamics and assumptions, which would help to better understand the model outputs, especially those unexpected or nonlinear results (Zhuge et al., 2019d).

As shown in Fig. 1, the EV market model is the core module of SelfSim-EV and simulates the interactions between the three core agent types in the vehicle market, namely Consumer, Manufacturer and Government Agents. Here, the decision-making of a consumer agent on vehicle purchase is simulated with a utility function considering four typical influence factors, namely environmental awareness, vehicle usage, vehicle price and social influence, based on the empirical findings in Beijing (Zhuge and Shao, 2019). It is worth noting that the vehicle choice of a consumer agent is also constrained by a fixed number of vehicle purchase permits specified in the license plate lottery policy. The four influential factors change over time, which are simulated and quantified as follows (see Fig. 1):

- **Vehicle Usage:** is used to describe the extent to which drivers are satisfied with their vehicles that can be either CV or EV, considering driving experience (e.g., range anxiety), travel time, fuel cost, etc. It is quantified based on the Activity-based Travel Demand Model,

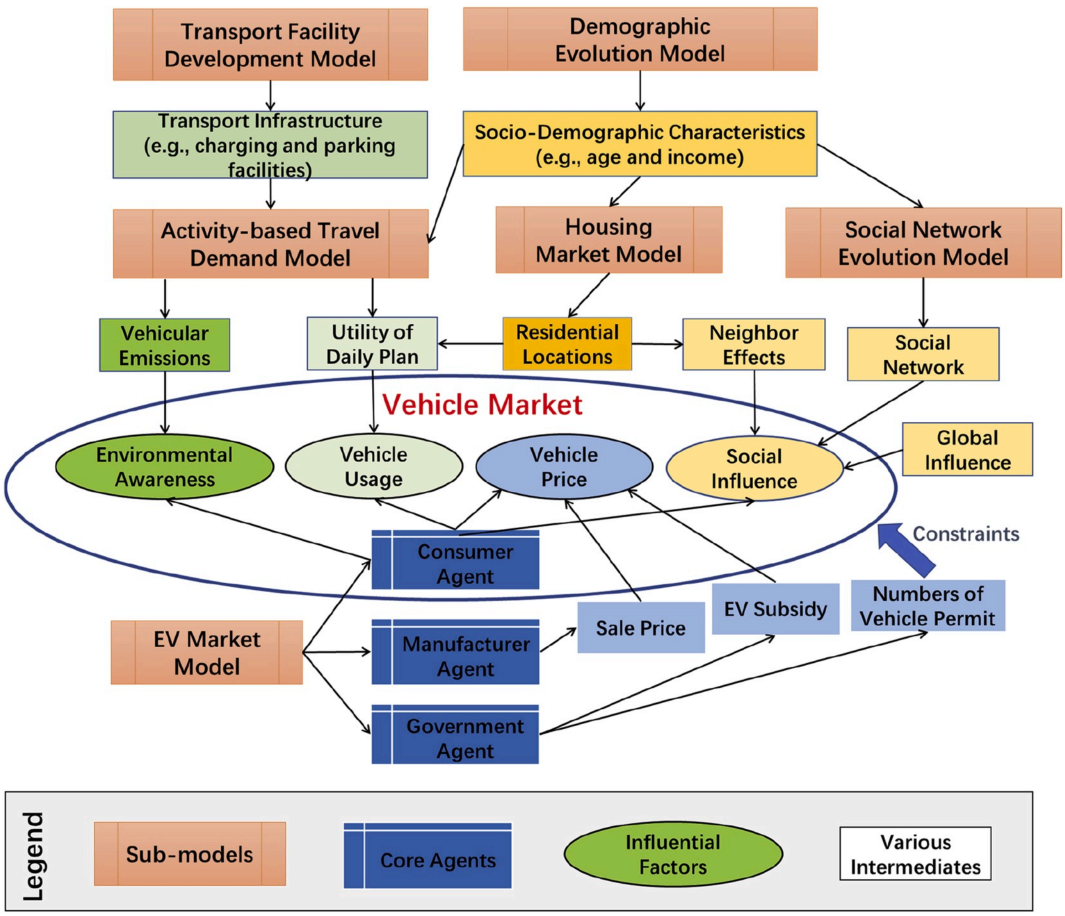


Fig. 1. Dynamics and interactions within a SelfSim-EV simulation (source: Adapted from (Zhuge et al., 2019d)).

which simulates how a person agent (e.g., driver) performs its daily activities (e.g., work and leisure) and travels from one activity location (e.g., workplace) to another (e.g., home). Each driver in SelfSim-EV has a daily plan which contains information on their travel and daily activities. Here, the utility of a daily plan is used to quantify vehicle usage. As shown in Fig. 1, the Activity-based Travel Demand Model is connected to both the Transport Facility Development Model and Demographic Evolution Model, as transport infrastructures and socio-demographic attributes (e.g., income) of a driver agent are influential to travel behaviour/demand of both CV and EV. For example, the availability of charging and parking facilities can influence individual travel behaviour or demand and further whether or not to purchase EVs; Also, socio-demographic attributes are associated with various decision-makings in the parking and charging events of CV and EV, and thus can also influence vehicle purchase of consumer agents through vehicle usage. Furthermore, the Activity-based Travel Demand Model is also connected to the Housing Market Model (specifically, a joint model of residential location choice and real estate price model: see (Zhuge and Shao, 2018b)), as the model simulates the residential relocation of household agent, which influences activity patterns of a driver agent. For example, residential relocation would change commuting time and thus the preferences of household agent towards EVs again through vehicle usage.

- **Environmental Awareness:** is quantified using the total amount of vehicular emissions (e.g., CO and HC), which is calculated also based on the Activity-based Travel Demand Model. Specifically, the model is updated from the MATSim-Beijing model (Zhuge et al., 2019c) by incorporating EV components (e.g., charging behaviour module). The simulation can obtain the moving trajectories of each driver (with either CV or EV), as well as the associated energy consumption and vehicular emissions at the link level, which can be further aggregated at the city level.
- **Vehicle price:** is the difference between vehicle sale price and possible EV subsidy, which are set by the manufacturer and government agents, respectively, according to the numbers of EV purchasers and owners.
- **Social Influence:** is composed of three typical types, namely global influence, neighbour effects and social network (or those influences through friendships). For neighbour effects, it is assumed that those people living around EV owners within a specific radius may be more likely to purchase EVs. Therefore, the quantification of neighbour effects is associated with residential location (or the Housing Market Model). In terms of social network, EV owners may have a positive influence on the EV adoption of their friends, and thus EV may diffuse through individual social networks. It is worth noting that spatial closeness of a pair of agents could influence whether and how they build and dissolve their friendships. Thus, social network is associated with residential location as well.

Among the above influential factors to the diffusion of EV, vehicle usage (including type of fuel used and electric driving range), environmental awareness (i.e., vehicular emissions) and vehicle price (including vehicle sale price and EV subsidies) are related to vehicle characteristics. It is worth noting that all these vehicle characteristics may vary across scenarios and over time, primarily due to the interactions and dynamics found in the system. Take vehicle sale price as example, the price is set by a vehicle manufacturer agent in the vehicle market according to vehicle penetration rates. In return, it can also influence the consumers' vehicle choice through the utility function and further vehicle penetration rates.

From a dynamic perspective, all the four influential factors above change over time, due to the evolution of those connected elements, including social networks, residential locations, transport infrastructures, socio-demographic attributes and daily plans. Take residential location as example, residential relocation of a household would change daily plans of each of its household member and also the so-called neighbour effects. Both could influence whether the household would purchase a vehicle or not and if yes, which vehicle type to choose.

In addition, several assumptions have been made in SelfSim-EV, especially on behavioural rules of agents. Specifically, utility maximization theory (Aleskerov et al., 2007) is a typical approach to simulating individual decision-makings in agent-based models, with the assumption that agents always choose the alternative which can maximize their utilities. The theory is used to define behavioural rules of several agent types (e.g., consumer and driver agents) through utility functions or discrete choice models. For example, utility functions are used to simulate vehicle purchase and residential location of household agents in the dynamic vehicle and housing markets, respectively. Several different Multinomial Logit Models (one type of discrete choice model) are used to simulate parking and charging behaviours of CVs and EVs in the Activity-based Travel Demand Model (Zhuge et al., 2019a, 2019b, 2019c).

3.2. Evaluating license plate lottery policies within “what-if” scenarios

3.2.1. Developing “what-if” scenarios through semi-structured interviews

“What-If” scenario analysis is a typical approach to evaluating a policy with different settings. However, it remains a challenge to set up reasonable scenarios that can exactly predict futures, due to huge uncertainty around policy making and urban dynamics. In order to understand the uncertainties in shaping EV-related policies (including the license plate lottery policy) and develop reasonable “what-if” scenarios, we conducted semi-structed interviews with 11 EV-related stakeholders in Beijing from September 2015 to March 2016, including 3 staff from EV manufacturers and 8 from local authorities. Since the license plate lottery policy is more relevant to the work of local authorities, only the personal viewpoints from the 8 staff are used here. Note that the viewpoints are personal and thus should not be linked to any local authorities. Based on the semi-structured interviews and also recent EV policies in China, this work sets up two types of “what-if” scenario below to explore the role of license plate lottery policy in the diffusion of EVs.

- **Scenario A:** aims to examine whether exclusive PHEV permits would promote the uptake of PHEVs, as currently PHEV purchasers does not receive any incentives in the license plate lottery policy in Beijing. However, in some other Chinese cities, such as Shanghai, PHEV purchasers receive the same benefits as BEV purchasers in the EV purchase policies (e.g., car license auction policy). As per the auction policy in Shanghai, both PHEV and BEV purchasers can get a license for free. Therefore, the outcomes of Scenario A would be useful for local authorities to adjust the license plate lottery policy to promote the development of PHEVs as well.
- **Scenario B:** is used to quantify the potential influence of more vehicle purchase permits on the uptake of both PHEVs and BEVs. Although the total number of vehicle permits was decreasing and is likely to decrease in a short term, the license plate lottery policy may be adjusted from time by time (and even be completely removed). For example, a recent EV policy by the central government of China suggested that local governments should not put restrictions on the purchase of new energy vehicles, including EVs. Furthermore, the semi-structured interviews also suggested that the license plate lottery policy was mainly used for mitigating traffic congestion and thus might be adjusted by adding more permits or even be totally removed when traffic condition is heavily improved, for example, due to a dramatic increase in the modal share to public transport.

3.2.2. Simulating “what-if” scenarios with SelfSim-EV

SelfSim-EV has been applied to simulate the evolution of EV market in Beijing, as detailed in (Zhuge et al., 2019d): it was firstly calibrated from 2011 to 2014 and then further validated in 2015. Then a Reference Scenario (RefSc) or baseline was set up with the calibrated and validated model to explore the future of EVs in Beijing from 2016 to 2020, assuming that the urban system, including the EV market and its associated elements (e.g., infrastructures), would evolve as before.

In this paper, we will again use the calibrated and validated Beijing SelfSim-EV model to explore the role of license plate lottery policy within several different “what-if” scenarios (namely Scenarios A and B: see Section 3.2.1). In order to quantify the influence of the lottery policy on the diffusion of EVs, these “what-if” scenarios will be compared to each other, and also against the baseline (or RefSc) in our previous work. From a technical perspective, the calibrated and validated Beijing SelfSim-EV model needs to be modified in order to simulate different lottery policies. Specifically, the government agent in the EV market model (see Fig. 1) is responsible for the allocation of vehicle permits, and thus its behavioural rules of allocating permits will be modified in Scenarios A and B accordingly prior to a SelfSim-EV simulation. Once the number of permits by vehicle type is changed, the behaviours of the three core agents (i.e., consumer, vehicle manufacturer and government) in the EV market model may change according to their own behavioural rules. This would further lead to the changes in all the connected elements, such as the urban environment, population, land use and transport systems.

4. Case study of Beijing, China

The capital of China, Beijing was used a case study, as the license plate lottery policy has been in place in Beijing for around eight years. The lottery policy was issued in 2011. Ever since, the policy has changed over time, especially in terms of the number of vehicle purchase permits and the dedicated permits for EVs (see Fig. 2). Specifically, the total number of vehicle purchase permits levelled off from 2011 to 2013 and then went down in 2013. It again levelled off from 2014 to 2016. Since 2014, a specific number of permits have been exclusively allocated to BEV applicants, in order to promote the purchase of BEVs. The number of BEV purchasers was almost the same as the number of BEV permits after 2014. The remaining so-called CV permits are for both CV and PHEV purchasers. As aforementioned, PHEV in theoretical is one type of EV, but the PHEV and CV purchasers in Beijing share a fixed number of so-called CV permits, which had a decreasing trend from 2014 to 2016.

As aforementioned, a Beijing SelfSim-EV model, which was calibrated and validated from 2011 to 2015 (see (Zhuge et al., 2019d) for more details), will be used here to explore how the license plate lottery policy may influence the diffusion of EV from 2016 to 2020, within two different “what-if” scenarios: Scenario A will be used to investigate how vehicle allocation methods may influence the uptake of EVs (see Section 4.1 below); Scenario B will be used to quantify the influence of different vehicle permit numbers on the EV diffusion (see Section 4.2 below). In order to quantify their influences, these two “what-if” scenarios will be compared to a so-called Reference Scenario (RefSc) assuming that the EV market in Beijing and also its connected systems would evolve as before during the period: see (Zhuge et al., 2019d) for a detailed introduce to RefSc. We will cite some RefSc results in the following scenario analyses where relevant for comparison purpose. In order to mitigate stochastic effects, we run each scenario 10 times and used the average as the final outcome for subsequent analyses (Zhuge et al., 2019d).

4.1. Scenario A: Vehicle permit allocation methods

In the RefSc scenario, potential PHEV and CV purchasers share a fixed number of the so-called CV permits in the lottery policy, because PHEV also uses petrol and releases emissions in some cases. By contrast,

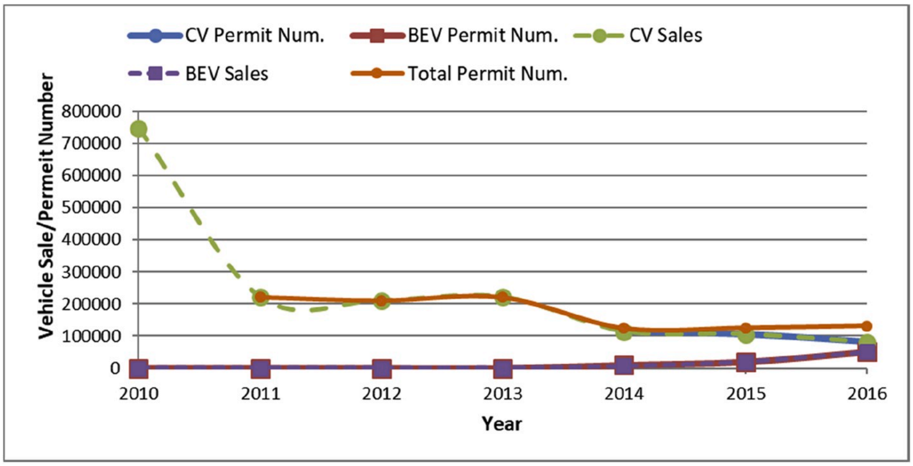


Fig. 2. Numbers of purchase permits and vehicle sales in Beijing from 2010 to 2016.

the "what-if" scenarios here will explore the influence of different vehicle allocation methods (i.e., exclusive PHEV permits) with the total number of vehicle permits fixed. These scenarios are described as follows (see Table 1):

- **Scenario 1 (PermitCVSc1):** splits the number of the so-called CV permits into two equal parts for CV and PHEV, respectively. Currently, PHEVs are not competitive with CVs in the Beijing market. This scenario is therefore to test whether exclusive PHEV purchase permits could increase the competitiveness of PHEVs.
- **Scenario 2 (PermitBEVSc2):** splits the number of BEV permits into equal parts for BEV and PHEV, respectively. Due to the range anxiety and lack of charging facilities, BEVs are not very favoured currently. This scenario is to examine if PHEVs may help to ease the transition.

4.1.1. EV market expansion in scenario A

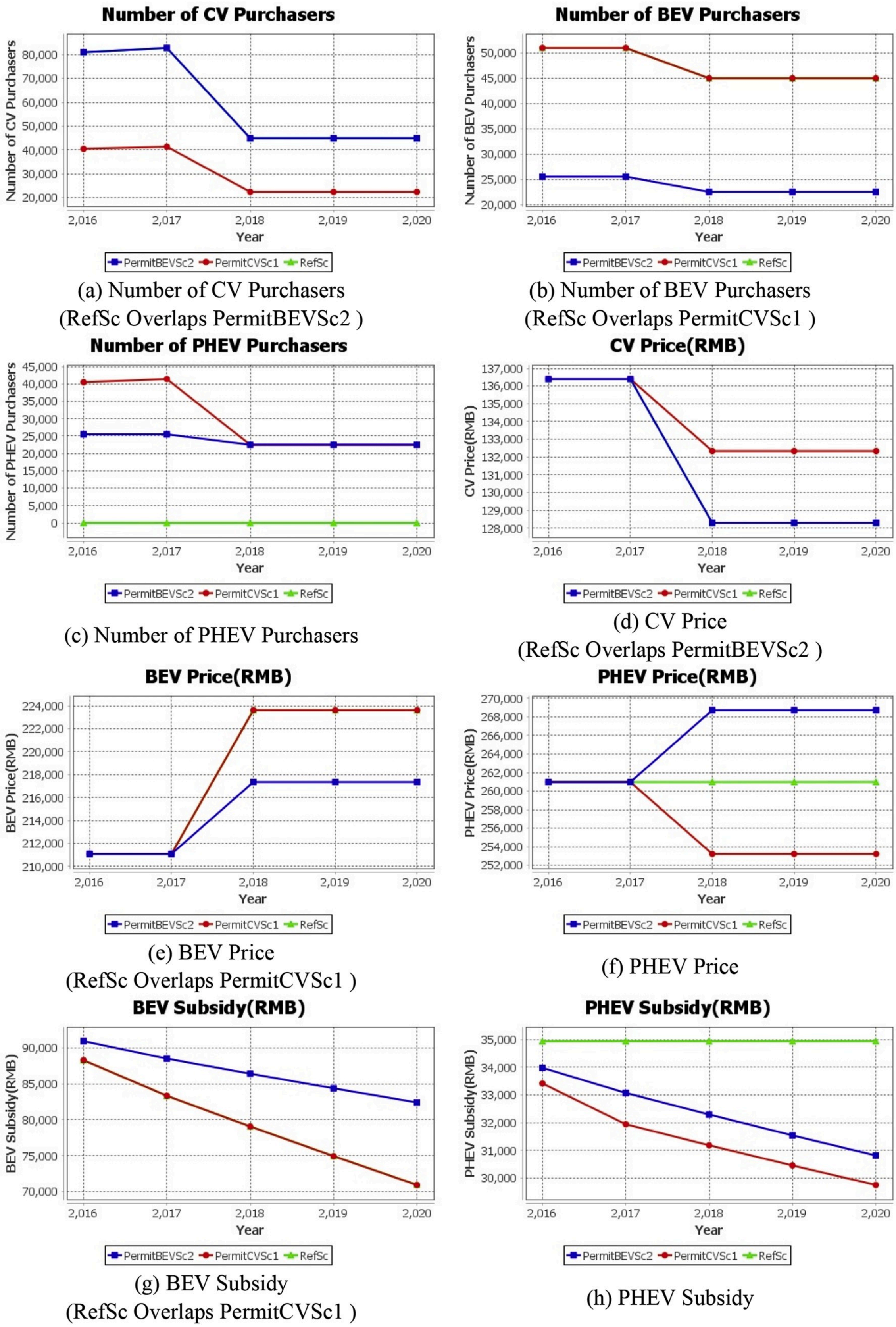
A comparison among the RefSc, PermitCVSc1 and PermitBEVSc2 scenarios is first carried out in terms of the EV market from 2016 to 2020. As shown by Fig. 3-(c), the numbers of PHEV purchasers in both PermitCVSc1 and PermitBEVSc2 go up because some PHEV purchase permits are particularly allocated. Accordingly, the numbers of CV purchasers in PermitCVSc1 and BEV purchasers in PermitBEVSc2 decrease due to the decrease of purchase permits allocated. In terms of vehicle prices, PermitCVSc1 has higher CV and BEV prices than RefSc and PermitBEVSc2, respectively, because the CV penetration rates in 2018 in the latter two scenarios decrease much more heavily than that in PermitCVSc1, which results in relatively higher CV price in PermitCVSc1, though the CV prices in all scenarios go down in 2018. Similarly, the BEV prices in all scenarios rise in 2018 because of the increase of BEV penetration rates. However, the BEV prices in PermitCVSc1 and RefSc go up more heavily due to the bigger increase in the BEV penetration rates. For the PHEV prices shown in Fig. 3-(f), the PHEV price in RefSc almost remains the same over the period, while the PHEV prices in PermitCVSc1 and PermitBEVSc2 go down and up, respectively, because of the decrease and increase in the PHEV penetration rates. In terms of EV subsidies, the BEV subsidies in all scenarios decrease because of the increasing BEV adoption rates. However, the BEV subsidy in PermitBEVSc2 is higher than those in the other two scenarios because the BEV adoption rates are relatively lower in PermitBEVSc2 due to the smaller number of BEV permits allocated. The PHEV subsidies in both PermitCVSc1 and PermitBEVSc2 decrease owing to their increasing PHEV adoption rates. PermitCVSc1 has lower subsidy because of its relatively higher adoption rate.

As a simulation model, SelfSim-EV also contains several behavioural rules of agents that are involved in randomness. For instance, the utility function for the decision-making of consumer agents on vehicle choice contains a random term following a Gumbel distribution (see (Zhuge et al., 2019d) for the utility function). Such randomness may influence the model outcomes. In order to reduce the potential stochastic effects, the average of the 10-run simulation results was used as the final outcomes, as aforementioned. Here, we use Standard Deviation (SD) to quantify the stochastic effects. The SD results about the EV market (see Figure A- 1 in Supplementary Material) suggest that the stochastic effects tend to be relatively slight.

In addition, the spatial differences between the RefSc and Scenario A in the number of vehicle owners (or the number per unit area) in 2020 were first quantified with the indicator of Relative Difference Ratio (RDR) and were then mapped at facility-, traffic zone- and district –levels, based on the residential locations of vehicle owners (see Figure A- 2, Figure A- 3 and Figure A- 4 in Supplementary Material for more details, respectively). The maps suggest that the ways to allocate the vehicle purchase permits could heavily influence the spatial distributions of vehicle owners at multiple resolutions (note that the number of vehicle owners per unit area was used in those maps at the zone- and district-levels). Taking the spatial difference in PHEV owners for example (see Fig. 4), with the increase in the number of PHEVs owners in both PermitCVSc1 and PermitBEVSc2, most of the traffic zones tend to have more PHEV owners, with few exceptional cases where the numbers of PHEV owners decrease (see those zones in red). The

Table 1
Scenarios for different vehicle permit allocation methods (Zhuge et al., 2019d).

Year	Reference Scenario (RefSc)		Scenario 1 (PermitCVSc1)			Scenario 2 (PermitBEVSc2)		
	CV	BEV	CV	PHEV	BEV	CV	PHEV	BEV
2016	81,000	51,000	40,500	40,500	51,000	81,000	25,500	25,500
2017	82,800	51,000	41,400	41,400	51,000	82,800	25,500	25,500
2018	45,000	45,000	22,500	22,500	45,000	45,000	22,500	22,500
2019	45,000	45,000	22,500	22,500	45,000	45,000	22,500	22,500
2020	45,000	45,000	22,500	22,500	45,000	45,000	22,500	22,500



(a) Number of CV Purchasers (RefSc Overlaps PermitBEVSc2)

(b) Number of BEV Purchasers (RefSc Overlaps PermitCVSc1)

(c) Number of PHEV Purchasers

(d) CV Price (RefSc Overlaps PermitBEVSc2)

(e) BEV Price (RefSc Overlaps PermitCVSc1)

(f) PHEV Price

(g) BEV Subsidy (RefSc Overlaps PermitCVSc1)

(h) PHEV Subsidy

Fig. 3. The EV Market from 2016 to 2020 in Scenario A and RefSc (Note that RefSc Results are from (Zhuge et al., 2019d)).

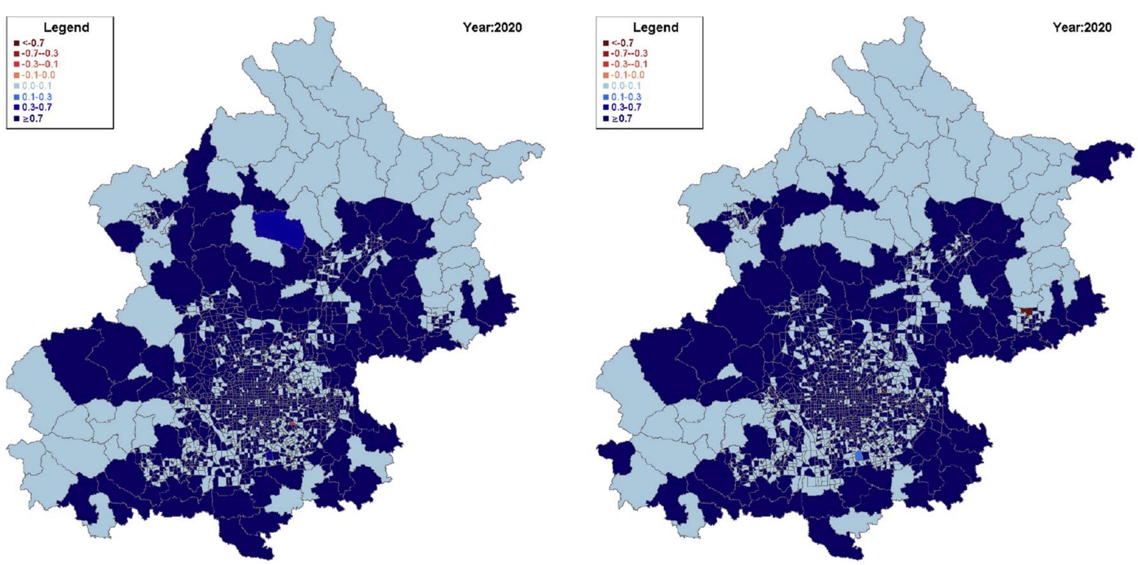
exceptional cases could be caused by several different factors. Two possible factors are discussed as follows: First, the allocation methods could change the decision-making of potential PHEV purchasers through the internal interactions among CV, PHEV and BEV purchasers in the vehicle market. For instance, some of those PHEV purchasers in RefSc might change their vehicle choices in Scenario A (i.e., PermitCVSc1 and PermitBEVSc2) and choose CV or BEV instead; 2) From a dynamic perspective, the decrease in the number of PHEV owners in some specific zones might be attributed to the residential relocation of PHEV owners. In other words, a PHEV owner might move to another zone, which results in the decrease. In addition, it can also be found from the maps that those zones in the central districts and the centre of the outer districts tend to have more PHEV owners. One possible reason might be that people living in these areas tend to have higher income and may be more likely to afford PHEVs, which have higher sale prices, due to no extra subsides from the Beijing government.

4.1.2. Impacts on the EV-related infrastructures in scenario A

The diffusion of EVs is closely associated with the EV-related infrastructures, including refuelling stations, parking lots, charging posts and charging stations, in terms of quantity, layout and usage. PermitCVSc1, which increases the number of PHEV purchasers with the number of BEV purchasers fixed, can significantly increase the demand for public charging posts, as shown by Fig. 5-(b). Compared to RefSc, PermitBEVSc2, which transfers the BEV permits into PHEV permits, decreases a little bit the demand for the public charging posts, as the PHEV drivers can also use petrol and rely less on electricity. This further decreases the total demand for charging posts. For the public parking spaces, the PermitCVSc1 scenario gets more parking spaces after 2018, which is likely to be associated with the travel patterns of vehicle drivers, rather than the number of vehicle purchasers, because the total numbers of vehicle purchasers are the same across the scenarios due to the constraint on the total number of vehicle permits. For instance, the vehicle purchasers in PermitCVSc1 might have more car-based trips and thus higher parking demand, which results in the higher number of public parking spaces.

In addition, the vehicle allocation methods could also influence the layouts of both public parking lots and charging posts at the zone- and district-levels, as shown by Figure A- 5-Figure A- 8 in Supplementary Material. The development of public parking lots and charging posts (see Fig. 1) is simulated within the Transport Facility Development Model according to parking and charging demands, respectively, which are obtained from the activity-based travel behaviour simulation within MATSim-EV, as described in detail in the work of (Zhuge and Shao, 2018a). Therefore, both the quantity and layout of the EV-related transport facilities could be influenced by EV penetration rates through travel patterns and behaviours. Specifically, the vehicle allocation methods can influence both the number and spatial distribution of vehicle owners, as shown by Figs. 3 and 4, respectively. Different vehicle owners could have completely different socio-demographic characteristics (e.g., employment status, income and marriage status) and travel demands (i.e. daily plans), which could heavily influence travel patterns and behaviours (e.g., commuting patterns) and further the number and layout of EV-related transport facilities, including public parking spaces and charging posts. More importantly, all these connected elements (e.g., vehicle ownership, travel demand and socio-demographic characteristics) evolve over time, making the system rather dynamic and complicated.

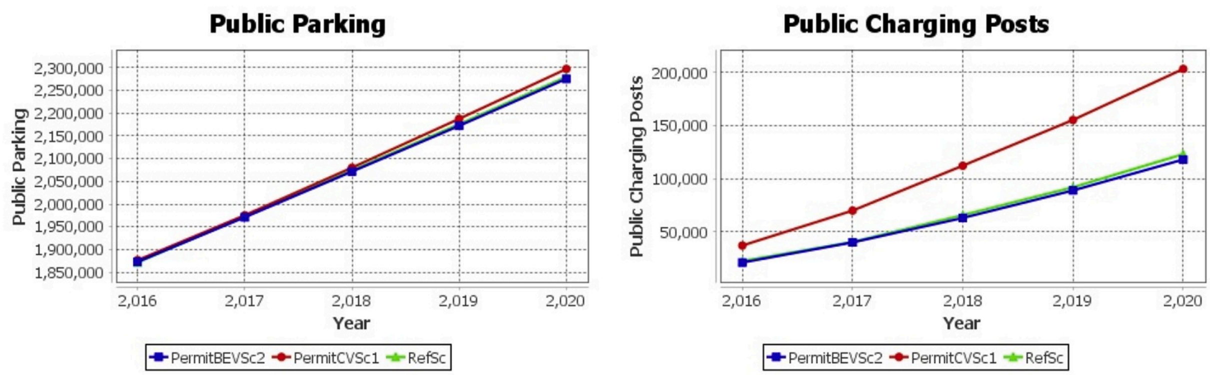
Taking public charging posts as example (see Fig. 6), both PermitCVSc1 and PermitBEVSc2 have significantly different layouts of charging posts at the district level: 1) all of the 16 districts in PermitCVSc1 have more charging posts in 2020 than RefSc, because the total number of public charging posts added increases heavily, as shown by Fig. 5-(b). Those central districts tend to have higher number of charging posts per unit area, as probably these districts tend to have relatively higher number of activity facilities (e.g., shops and workplaces) and thus higher travel demand, which could give rise to the higher charging demand from EVs; 2) Due to the slight decrease in the total number of public charging posts in 2020 in PermitBEVSc2 (see Fig. 5-(b)), the majority of the districts (especially those outer districts) get less public charging posts. However, the three central districts get more public charging posts, which is not generally expected. This could be directly and indirectly caused by several different factors. Two specific possible factors are discussed as follows: First, it might be attributed to the specific travel patterns of PHEV owners which tend to have higher number of daily activities (e.g., shopping) performed at these central



(a) Difference between PermitCVSc1 (more PHEVs but less CVs) and RefSc in PHEV Owners

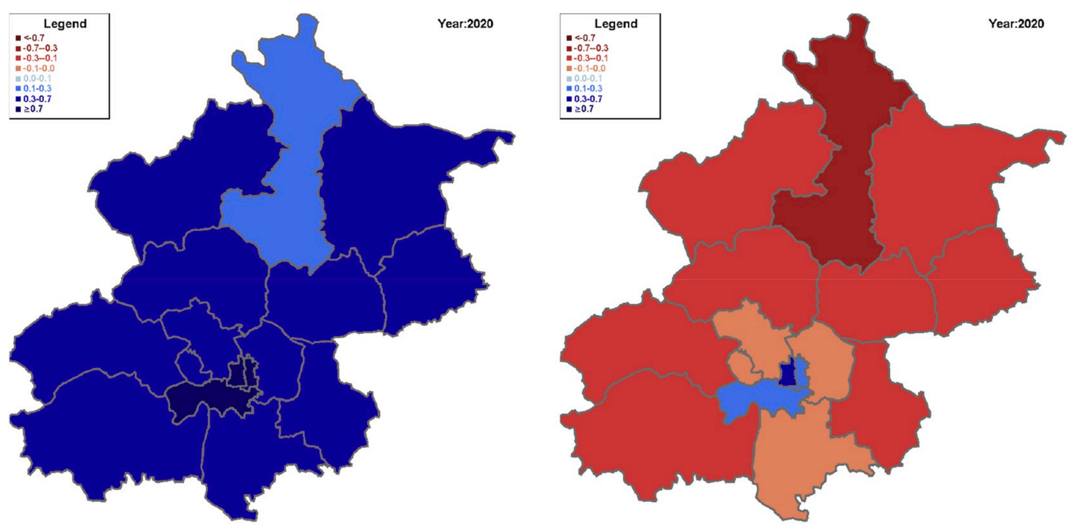
(b) Difference between PermitBEVSc2 (more PHEVs but less BEVs) and RefSc in PHEV Owners

Fig. 4. Spatial differences between scenario A and RefSc in the number of PHEV owners per unit area in 2020 (Zhuge et al., 2019d).



(a) Number of Public Parking Spaces (b) Number of Public Charging Posts

Fig. 5. Impacts of EV Market on Transport Infrastructures from 2016 to 2020 in Scenario A and RefSc (Note that RefSc Results are from (Zhuge et al., 2019d)).



(a) Difference between PermitCVSc1 (more PHEVs but less CVs) and RefSc in Public Charging Posts

(b) Difference between PermitBEVSc2 (more PHEVs but less BEVs) and RefSc in Public Charging Posts

Fig. 6. Spatial differences between scenario A and RefSc in the number of public charging posts per unit area in 2020 (Zhuge et al., 2019d).

districts. This could lead to higher travel and charging demands and thus more public charging posts; Second, PermitBEVSc2 has significantly different geographical distributions of BEV and PHEV owners (see Figure A- 2, Figure A- 3 and Figure A- 4 in Supplementary Material) according to their residential locations. The changes in residential location could also influence travel patterns of EV owners. These three central districts might get more EV owners (especially PHEV owners, see Fig. 4), and thus higher travel and charging demands, which could give rise to more public charging posts.

4.2. Impacts on the environment in scenario A

Essentially, it can be found from Fig. 7 that PermitBEVSc2 consumes more petrol and produces more vehicular emissions because it transfers half of the BEV purchaser permits into PHEV permits, which eventually gives rise to more petrol consumed and more emissions released by PHEV drivers. In the PermietCVSc1 scenario, since half of the CV permits are transferred into PHEV permits, the PHEV drivers can use electricity in some cases, and thus less petrol might be consumed and less vehicular emissions are released. Another possible reason why the amount of petrol consumed decreases in PermietCVSc1 is because the travel pattern of CV owners changed due to the internal interaction among CV, PHEV and BEV purchasers in the vehicle market and also the external interaction between CV travel demand and the connected urban elements, such as residential location and demographic evolution (e.g., employment status). For instance, the CV owners in PermietCVSc1 could have different residential locations, compared to RefSc (see Figure A- 2-(c) in Supplementary Material). This could give rise to the changes in travel patterns of CV (e.g., commuting pattern) in PermietCVSc1 and further the decrease in the amount of petrol consumed.

Furthermore, the impacts on the environment in Scenario A and RefSc can be compared at the street- zone- and district levels (see Figure A- 9 and Figure A- 10 in Supplementary Material for more details). Fig. 8 compares the spatial differences between the RefSc and Scenario A in the amount of vehicular emissions per unit area in 2020, suggesting that PermitBEVSc2, which allocates half of the BEV permits to PHEV purchasers, could to some extent increase the total amounts of vehicular emissions in all of the 16 districts, with an increasing rate ranging from 0% to 10% in 2020. For PermitCVSc1, it could also to some extent change (either increase or decrease) the amount of vehicular emissions of each district.

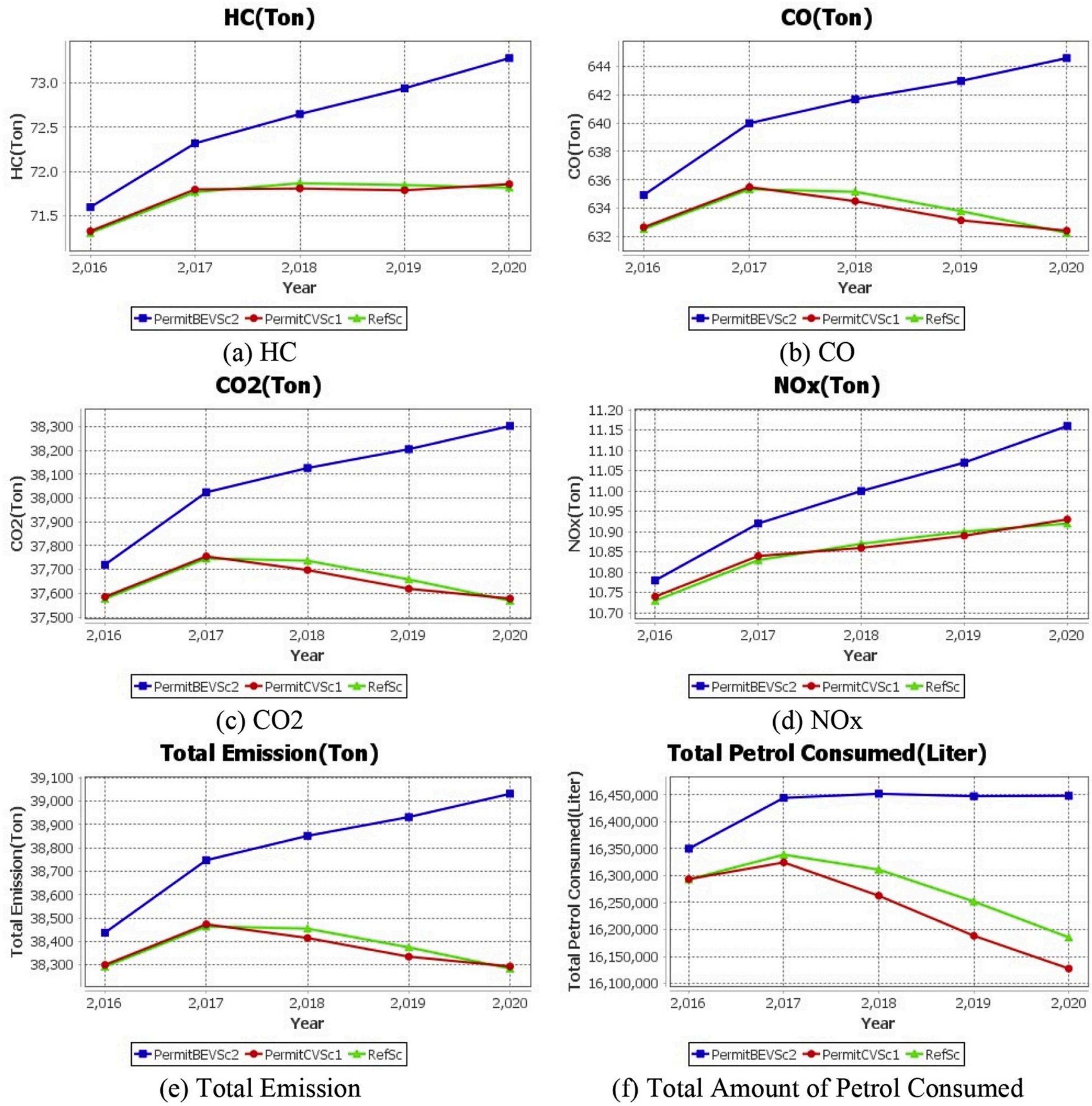


Fig. 7. Total Amounts of Petrol Consumed and Vehicular Emissions in One Particular Weekday in PermitCVSc1(more PHEVs but less CVs), PermitBEVSc2 (more PHEVs but less BEVs) and RefSc from 2016 to 2020 (Note that RefSc Results are from (Zhuge et al., 2019d)).

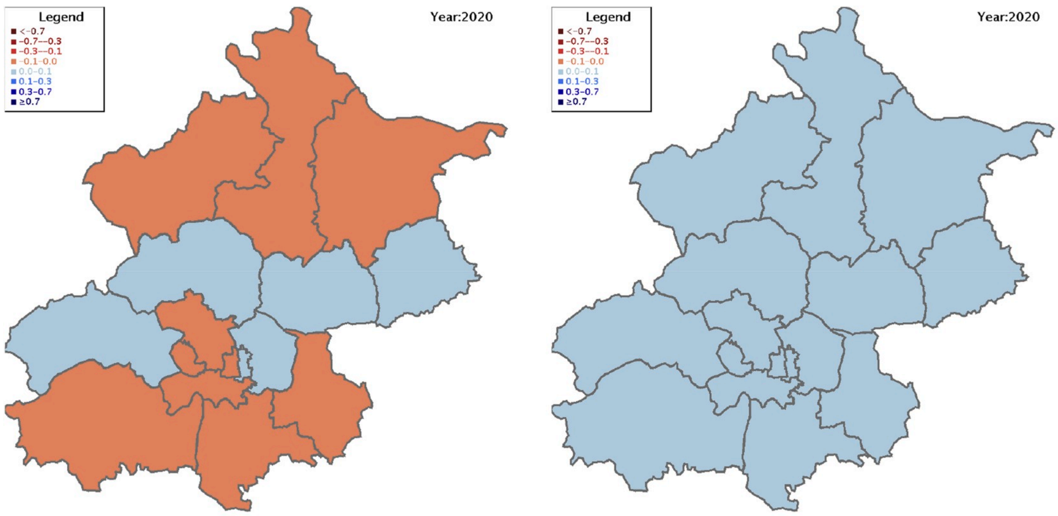
4.2.1. *Impacts on the power grid system in scenario A*

Fig. 9 compares the electricity consumed through charging posts at both public and private parking lots in Scenario A and RefSc. For PermitBEVSc2, it consumes less electricity provided by both public and private charging posts, because the scenario has less BEVs than the other two scenarios, though some PHEVs are added. However, the total amount of electricity consumed in PermitCVSc1is less than that in RefSc in 2020 (see Figure A- 11 in Supplementary Material), though more PHEVs are added to PermitCVSc1. The difference is around 175,000 kW·h. This unexpected result could be directly and indirectly caused by many factors. We discuss three possible causes or factors as follows:

(1) Residential Location of Vehicle Owners: could be a likely factor. As shown in Figure A- 3 in Supplementary Material, PermitCVSc1 has a significant different geographical distributions of CV, PHEV and EV owners, compared to RefSc. Since residential location is generally the origin and destination of the first and last trips of each vehicle owner, respectively, the changes in the residential locations of vehicle owners could result in different travel and charging behaviours of EVs. For instance, the changes in residential location of BEV owners (see Figure A- 3-(a)) could result in different travel patterns of BEV owners, such as commuting patterns, and further the decrease in amount of electricity consumed through charging posts. It is commonly recognized that the residential location and workplace is highly correlated (Waddell, 1993).

(2) Traffic Pattern: might be another possible cause. Specifically, the amount of electricity consumed is closely associated with travel speed (or traffic condition). As shown by Figure A- 12, PermitCVSc1 differs significantly from RefSc in traffic pattern (described with the ratio of traffic volume to link capacity), which could give rise to the change (i.e. decrease) in the electricity consumption of EVs and further the decrease in the amount of electricity consumed through charging posts.

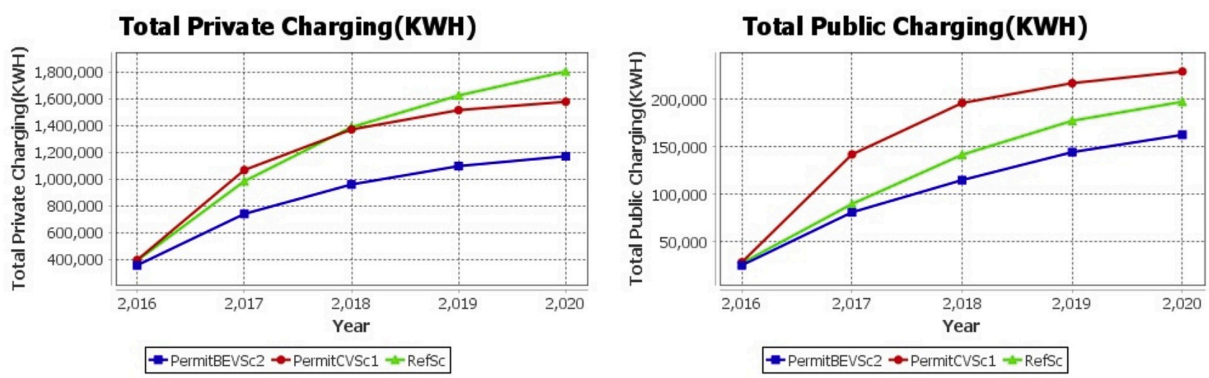
(3) EV-Related Transport Facilities. PermitCVSc1 has more PHEVs which may compete against BEVs for limited charging facilities at



(a) Difference between PermitCVSc1(more PHEVs but less CVs) and RefSc in Vehicular Emissions

(b) Difference between PermitBEVSc2 (more PHEVs but less BEVs) and RefSc in Vehicular Emissions

Fig. 8. Spatial Differences between Scenario A and RefSc in the Amount of Vehicular Emissions per Unit Area in one Particular Weekday in 2020 (Zhuge et al., 2019d).



(a) Electricity Consumed through Private Charging Facilities

(b) Electricity Consumed through Public Charging Facilities

Fig. 9. Total Amounts of Electricity Consumed through Charging Posts in One Particular Weekday in PermitCVSc1(more PHEVs but less CVs), PermitBEVSc2 (more PHEVs but less BEVs) and RefSc from 2016 to 2020 (kW·h) (Note that RefSc Results are from (Zhuge et al., 2019d)).

trip destinations, though more charging facilities were added to PermitCVSc1 (but might not be enough). This competition may lead to the decrease in the amount of electricity consumed by BEVs through public charging facilities. Furthermore, the layout of public charging facilities in PermitCVSc1 is completely different, compared to RefSc (see Fig. 6-(a)), which could influence charging behaviours of EVs and further the amount of electricity consumed through charging facilities. In addition, parking lots, which are the base of charging facilities, were also heavily influenced in terms of the layout, as shown in Figure A- 5-(a). The spatial changes in parking space could also give rise to the changes in parking and charging behaviours of EVs and further the amount of electricity consumed through charging facilities.

More importantly, all of these factors also interact with each other and change over time (see Fig. 1), which makes it more difficult to exactly point out the causes. For example, the changes in the number and layout of charging facilities would influence the utility of owning an EV (through the utility for vehicle usage), as charging facilities might become more accessible to some potential EV purchasers. This could lead to changes in the geographical distribution of EV owners and further their travel patterns, which could result in different charging demands. In return, the changes in charging demand would influence the quantity and layout of charging facilities.

In addition, the spatial differences between Scenario A and RefSc in the charging demand (see Figure A- 13, Figure A- 14 and Figure A- 15 in Supplementary Material for more details) suggest that both the allocation methods could heavily change the charging demand at the facility-, zone- and district-levels.

4.3. Scenario B: Vehicle permit numbers

Another five scenarios were set up to explore the influence of the number of vehicle permits on the EV diffusion. In general, it is hoped that the lottery policy can eventually reduce traffic congestion. Meanwhile, in order to promote the purchase of BEVs and improve air quality, a specific number of permits are exclusively allocated to BEVs. However, the number of vehicle purchase permits is far less than the demand and the policy has upset many potential purchasers. Therefore, the scenarios here are used to test what may happen when car ownership is increased. Compared with the RefSc scenario, these scenarios increase both CV and BEV permit numbers by different specific percentages of 10%, 30%, 50%, 70% and 100%. Table 2 summarizes the resulting numbers of CV and BEV permits for each scenario from 2016 to 2020. Note that CV and PHEV purchasers share a fixed number of the so-called CV permits.

4.3.1. EV market expansion in scenario B

First, the potential stochastic effects on the EV market expansion are examined, suggesting that the effects tend to be relatively low and may influence the results slightly (see Figure A- 16 in Supplementary Material for more details). Then, Scenario B and RefSc are further compared in terms of the number of vehicle purchasers, vehicle prices and EV subsidies (see Fig. 10): (1) Number of Vehicle Purchasers. For the number of BEV purchasers, it goes up with the increase of BEV permit number, and the number of purchasers is exactly equal to the number of permits. Similarly, the number of CV purchasers also goes up, as the number of CV permits rises, but the number of CV purchasers is slightly smaller than the number of CV permits, because PHEV purchasers also compete for the limited number of so-called CV permits and finally get a small fraction in the period from 2018 to 2020. Essentially, more CV permits could give rise to more PHEV purchasers. For example, the total number of PHEV purchasers in 2020 reaches above 4,000, when the number of CV permits doubles in PermitR100Sc7. (2) Vehicle Prices. The BEV prices are almost the same across all of the scenarios and they go up to around 224, 000RMB in 2018, which is the maximum price allowed to be set in the scenarios, and then level off. For the CV and PHEV prices, they behave oppositely because their penetration rates change oppositely. Specifically, the CV penetration rates become lower when more CV permits are added to the scenarios, but the PHEV penetration rates become higher, which further gives rise to the decrease of CV price, but the increase of PHEV price, as more CV permits are added. (3) EV Subsidies. As shown by Fig. 10-(g) and -(h), both BEV and PHEV subsidies go down when their adoption rates rise. Therefore, the more permits that are allocated, the lower subsidies they will be.

In addition, the spatial differences between Scenario B and RefSc in vehicle owners (see Figure A- 17, Figure A- 18 and Figure A- 19 in Supplementary Material for more details) suggest that the increase in the number of permits could essentially increase the vehicle owners to the majority of zones and districts, but some of them get less vehicle owners, likely due to both the internal interactions among potential purchasers in the vehicle market and also the external interactions between the vehicle market and those associated elements, such as population system and the dynamic housing market. Take the population system as an example, all person agents in the population need to update their socio-demographic characteristics. The changes in some of the socio-demographic attributes, such as income, employment status, marriage status and deaths, would give rise to household relocation and further the spatial distribution of vehicle owners. As a result, some zones and districts might get less vehicle owners.

4.3.2. Impacts on the EV-related infrastructures in scenario B

Compared with the RefSc scenario, it can be found from Fig. 11 that allocating more vehicle permits in Scenario B can significantly impact the numbers of public parking spaces and public charging posts. Further, the numbers of extra added public parking spaces and charging posts appear to be directly associated with the numbers of extra added vehicle purchase permits. This is because the development of transport facilities (either adding or removing facilities) is closely associated with the demand. In addition, the spatial differences between Scenario B and RefSc in the numbers of parking lots and charging posts suggest that the increase in the number of permits could essentially increase the transport facilities to the majority of traffic zones and districts with few exceptions, as shown by Figure A- 20 - Figure A- 23 in Supplementary Material. As discussed above, these exceptions could be attributed to many factors, such as the residential relocation, population evolution, and interactions among vehicle purchasers. Take residential relocation as an example, the changes in residential location of household would influence travel patterns of vehicle owners (e.g., commuting patterns), which could give rise to the changes in travel, parking and charging demands and further the layout of EV-related transport facilities. As a result, some traffic zones and districts might get less transport facilities due to the changes in demand (or essentially the residential relocation).

4.3.3. Impacts on the environment in scenario B

It is not surprising to find that adding more PHEVs and CVs can increase the total amount of petrol consumed, which further gives rise to the increase of vehicular emissions, including HC, CO, CO2 and NOx, as shown by Fig. 12. Furthermore, most of the traffic zones and districts in Scenario B tend to have higher amount of vehicular emission, as evident from the spatial differences between Scenario B and RefSc shown by Figure A- 24-Figure A- 26 in Supplementary Material.

4.3.4. Impacts on the power grid system in scenario B

As shown by Fig. 13, the amount of electricity provided through either private or public charging posts increases when more vehicle purchase permits are added. However, it can also be found that charging demand does not increase linearly. For example, in 2020, the total amounts of electricity provided by private charging posts in PermitR100Sc7 and RefSc are around 1,900,000 kW·h and 1,300,000 kW·h higher than that in 2016, respectively. It can be estimated that the private charging demand only increases by around 46% when the EV numbers are doubled in PermitR100Sc7. Again, this could be attributed to many factors, such as changes in travel patterns and traffic states, population evolution and residential relocation, as well as the interactions between these factors, as discussed above (see Section 4.1.4). Take travel pattern as an example, potential EV purchasers could save energy cost by using EVs. This could increase the utility of vehicle usage, which is one term in the utility function for decision-making on vehicle purchase. In RefSc, those EV purchasers tend to be those people with a longer car-based trip distance or higher car-based trip frequency, as they could save more energy cost and thus have a higher purchase utility with EVs. While in PermitR100Sc7 which doubles vehicle permits, those people with a shorter car-based trip distance or lower car-based trip frequency might also purchase EVs. As a result, the amount of electricity

Table 2
Scenarios for different numbers of vehicle permits from 2016 to 2020 (Zhuge et al., 2019d).

Year	Reference Scenario (RefSc)		Scenario 3 (10%, PermitR10Sc3)		Scenario 4 (30%, PermitR30Sc4)		Scenario 5 (50%, PermitR50Sc5)		Scenario 6 (70%, PermitR70Sc6)		Scenario 7 (100%, PermitR100Sc7)	
	CV	BEV	CV	BEV	CV	BEV	CV	BEV	CV	BEV	CV	BEV
2016	81000	51000	89100	51000	105300	66300	121500	76500	137700	86700	162000	102000
2017	82800	51000	91080	51000	107640	66300	124200	76500	140760	86700	165600	102000
2018	45000	45000	49500	45000	58500	58500	67500	67500	76500	76500	90000	90000
2019	45000	45000	49500	45000	58500	58500	67500	67500	76500	76500	90000	90000
2020	45000	45000	49500	45000	58500	58500	67500	67500	76500	76500	90000	90000

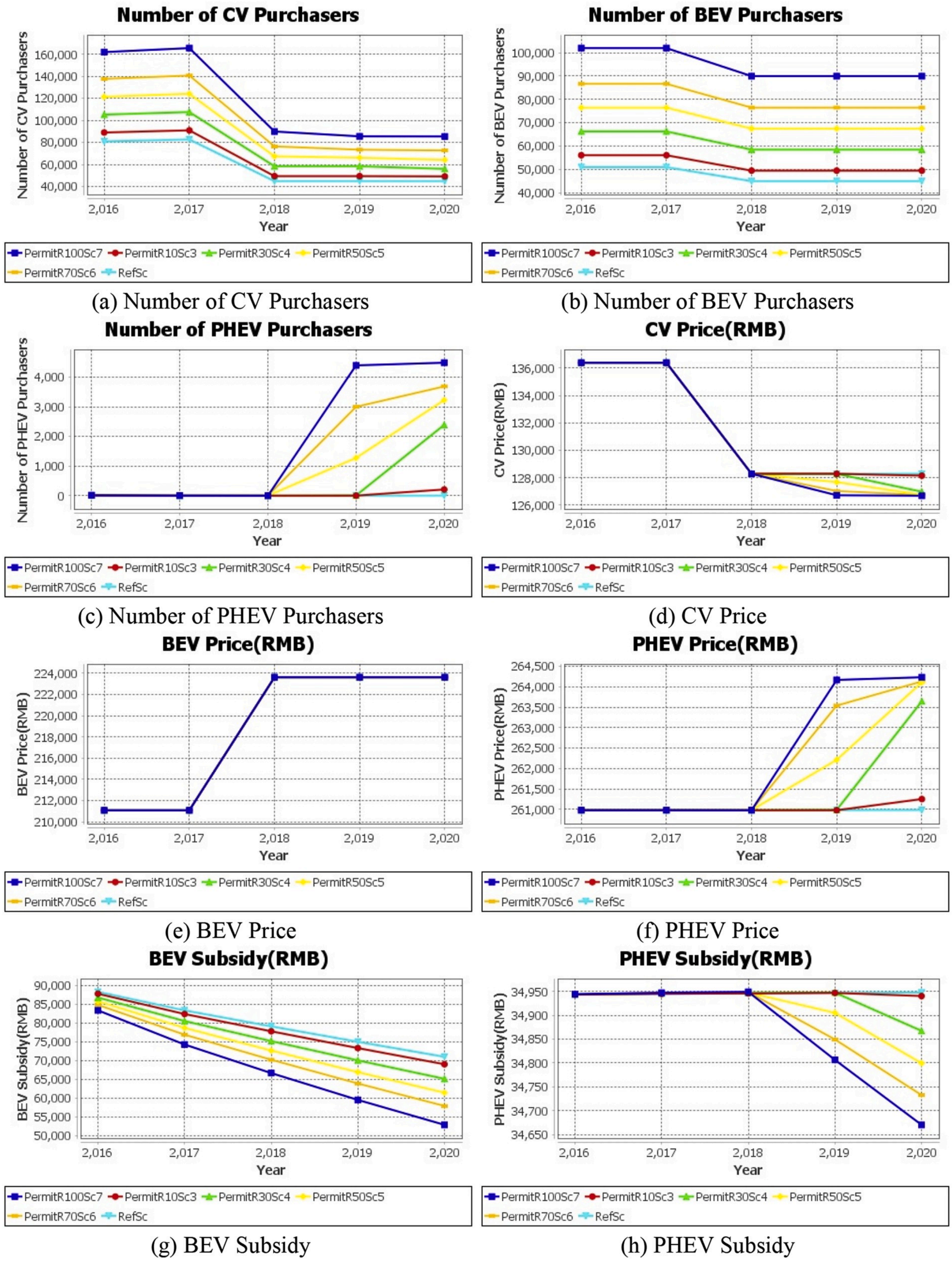
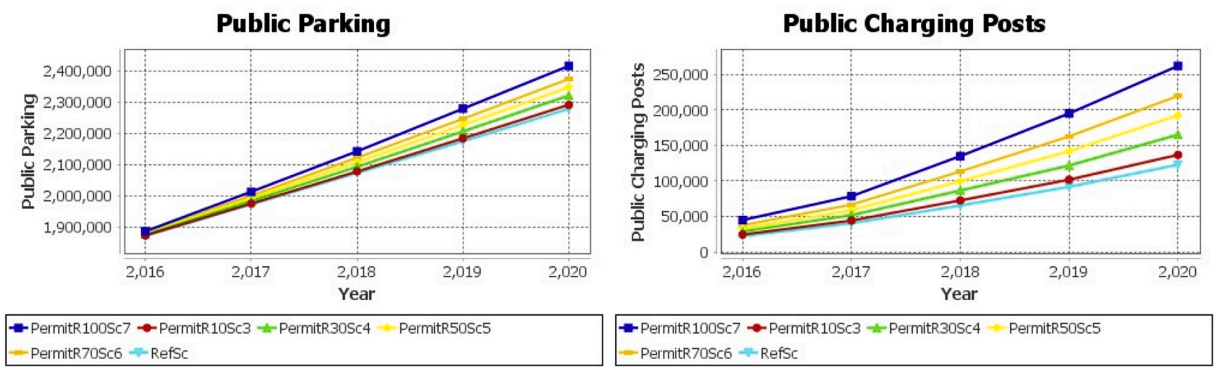


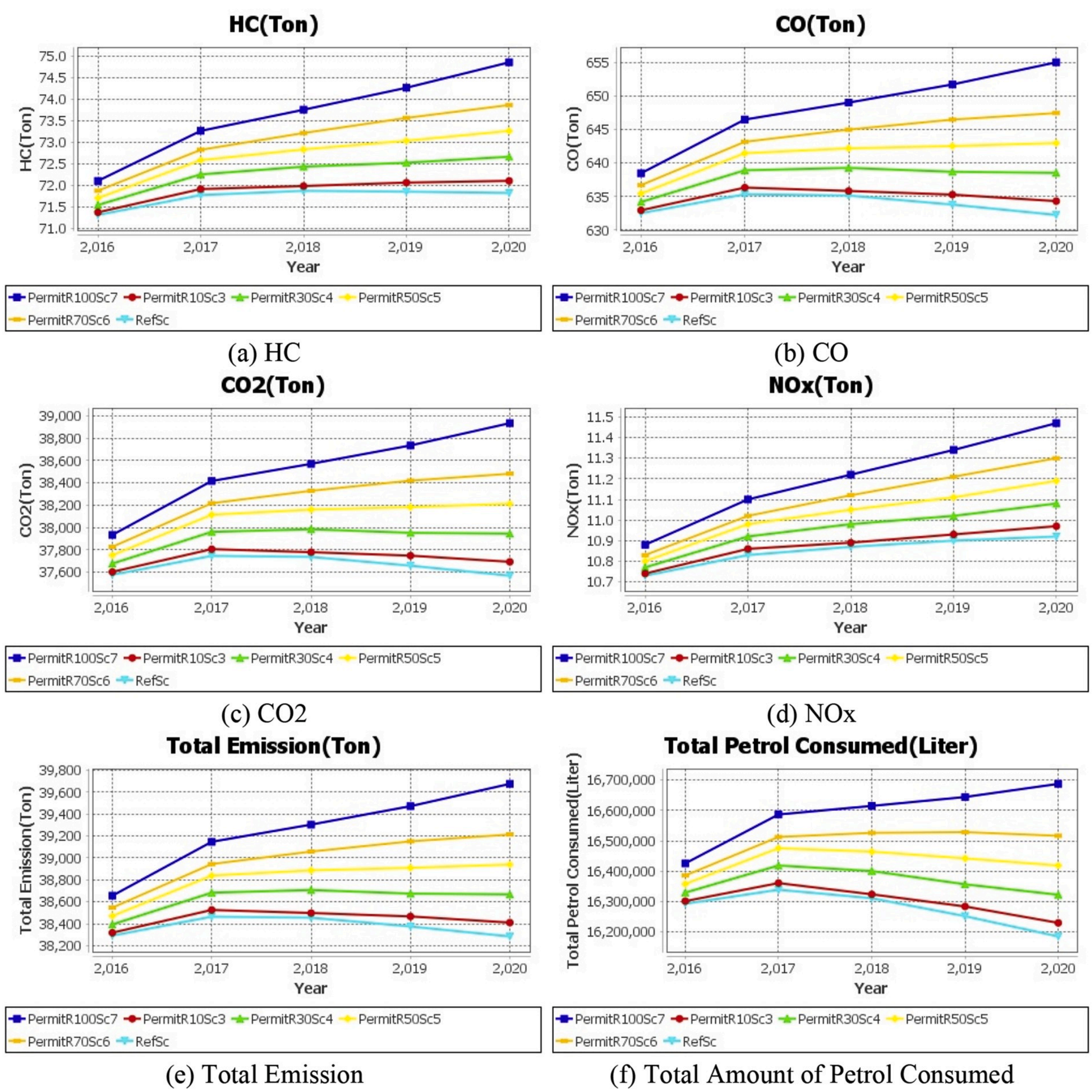
Fig. 10. The EV Market from 2016 to 2020 in Scenario B and RefSc (Note that RefSc Results are from (Zhuge et al., 2019d)).

consumed through charging posts does not increase linearly. In addition, the increase in the charging demand tends not to be distributed evenly across space, with most of the zones and districts having higher charging demand and few of them getting lower demand. This could be caused by both the internal and external interactions discussed above (see Section 4.2.2).



(a) Number of Public Parking Spaces (b) Number of Public Charging Posts

Fig. 11. Impacts of EV Market on Transport Infrastructures from 2016 to 2020 in Scenario B and RefSc (Note that RefSc Results are from (Zhuge et al., 2019d)).

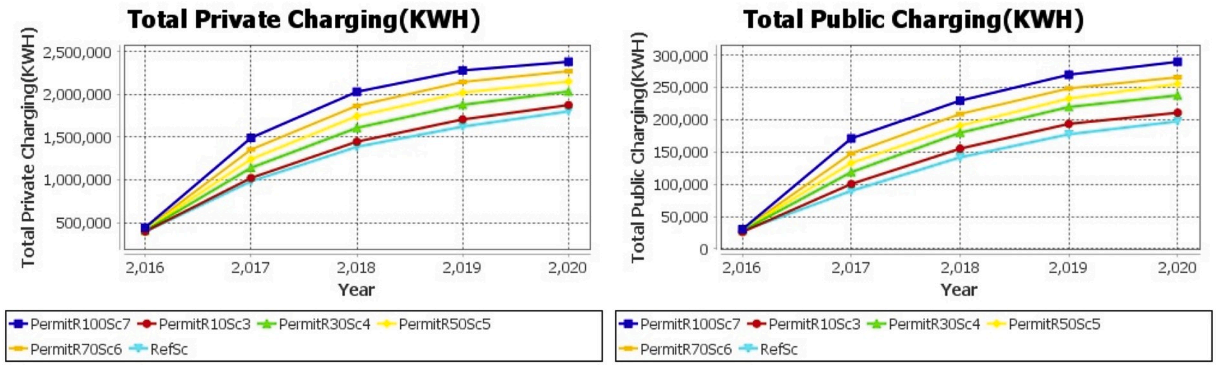


(a) HC (b) CO

(c) CO2 (d) NOx

(e) Total Emission (f) Total Amount of Petrol Consumed

Fig. 12. Total Amounts of Petrol Consumed and Vehicular Emissions in One Particular Weekday from 2016 to 2020 in Scenario B and RefSc (Note that RefSc Results are from (Zhuge et al., 2019d)).



(a) Electricity Consumed at Private Facilities (b) Electricity Consumed at Public Facilities

Fig. 13. Total Amounts of Electricity Consumed though Charging Posts in One Particular Weekday from 2016 to 2020 in Scenario B and RefSc (Note that RefSc Results are from (Zhuge et al., 2019d)).

5. Conclusion and policy implications

5.1. Policy implications

5.1.1. Suggestions to EV-related stakeholders

According to the "what-if" scenario analyses above (see Sections 4.1 and 4.2), both allocation methods and the number of vehicle permits in the license plate lottery policy are influential to uptake of EVs and also its associated elements, such as the urban environment, energy system and urban infrastructures, at both the micro- and macro-levels. The results from these "what-if" scenario analyses would be useful for different EV-related stakeholders involved (Zhuge et al., 2019e):

1) The Government: is suggested to carefully design or adjust the license plate lottery policy, and special attention needs to be paid to both the vehicle permit allocation method and the number of vehicle permits allocated, as these two factors are found as significantly influential to the uptake of EVs; Also, the policy is associated with both the total amount and spatial distribution of vehicular emissions; Therefore the potential local and global environmental impacts should be also be borne in mind. For example, the spatial distributions of different vehicular emissions at the multiple resolutions suggest the potential human health effects due to the exposure to the emissions;

2) Urban Planners: are suggested to take into account the potential implications of the policy on the quantity, layout and usage of the EV-related transport facilities, including slow charging posts at parking lots and refuelling stations, when they develop master plans for urban transportation system or the whole city;

3) Fuel Suppliers: are suggested to bear in mind the potential changes in the petrol demand from both CVs and PHEVs due to the changes in the allocation method or number of vehicle permits allocated, and then to distribute petrol efficiently to different refuelling stations, so as to accommodate the varying refuelling demand;

4) Grid Companies: should also take into account the potential influence on the charging demand from EVs at both public and private charging facilities. They may need to pay special attention to the changes in private charging demand at home. The reasons are twofold: first, private charging demand tends to much higher than public charging demand in all of the tested and RefSc scenarios (see subfigures (a) in Figs. 9 and 13); second, private charging demand in general occurs at nights when the domestic electricity demand is also relatively higher. The additional electricity demand from EVs may put pressure on the power grid system, and therefore grid companies need to take proper measures (e.g., time-of-use tariff policy and investment in power equipment). In addition, grid companies should also take into consideration the nonlinear relationship between the number of EVs added and the amount of electricity consumed through (see Fig. 13), and are suggested not to invest in power equipment simply according to the number of EV purchasers.

5) Vehicle Manufacturers: tend to more care about the policy implications, as their production strategy is closely associated with the number of vehicle permits. The historical data has suggested that the sales of both CV and EV were heavily influenced by the license plate lottery policy. Take CV sale for example, the number of CVs sold decreased heavily from around 748,000 in 2010 to 221,610 after the policy was issued, as shown in Fig. 2. Therefore, vehicle manufacturers may need to adjust their production plans according to the numbers of potential CV, PHEV and BEV purchasers.

Since the license plate lottery policy has been increasingly issued, especially in Chinese cities (e.g., Beijing, Tianjin, Hangzhou, Chengdu and Changsha), the results from this paper could also be useful for those cities using or potentially adopting the policy. In particular, for those cities adjusting or designing the policy, they are suggested to take into the two influential factors identified in this paper, namely the vehicle permit allocation methods and the number of vehicle permits allocated each time.

5.1.2. Policy marking considering assumptions, interactions, dynamics and uncertainties

In addition to the suggestions above to particular EV-related stakeholders, policy makers are also suggested to pay attention to model assumptions, interactions, dynamics and uncertainties when shaping license plate lottery policies, as they are closely associated with the diffusion of EV and also its connected elements (e.g., infrastructures and power grid system).

- **Model Assumptions:** as aforementioned, utility maximization theory has been used a primary approach to simulating various decision-makings of agents (e.g., purchase, parking and charging behaviours of EVs) in the SelfSim-EV simulation. In reality, agents might not be able to always choose the alternative which can maximize their own utilities, for example, due to the limited access to full information for their decision-makings. As a result, the assumptions might lead to biases about the diffusion of EV and its connected systems, which should be borne in mind when the outcomes are used in practise.
- **Model Interactions:** As shown in Fig. 1, the diffusion of EV interacts heavily with those connected urban elements, including travel demand, residential location, socio-demographic evolution, social influence and EV-related transport facilities. Specifically, the expansion of EV market would potentially influence these connected elements. Therefore, policy makers should not only look at the implication of the lottery policy on the uptake of EVs, but also take into consideration the further influences on these connected elements; In return, these connected elements would also influence the vehicle purchase behaviour at the individual level, through the four

typical factors, namely vehicle usage, vehicle price, environmental awareness and social influences. Therefore, policy makers should take these connected elements into account when adjusting the lottery policies. For example, residential location could influence the purchase behaviour of EV through both travel patterns (e.g., commuting patterns) and the so-called neighbour effects. Furthermore, residential location is also associated with spatial distributions of vehicular emissions and charging demand of EV. Therefore, residential location of potential vehicle purchasers should be considered in policy making.

- **Model Dynamics:** Urban system is a typical complex and dynamic system. Due to the evolution of urban system, including the EV market and its connected urban sub-systems (e.g., transportation and land use), the purchase, travel, and charging behaviours of EV would change over time. Dynamics could make the interactions above become more complicated, as all the interactions would also evolve over time and across space. As a result, the diffusion of EV and its connected elements, such as the urban environment (e.g., vehicular emissions), power grid system (e.g., electricity consumption) and EV-related transport facilities could be heavily influenced. Therefore, policy makers are suggested to shape or adjust the lottery polices from a dynamic perspective, considering the interactions over time.
- **Model Uncertainties:** There are several different types of uncertainty around policy making, which could be attributed to model parameters, model structure, future events and also acknowledged and unknown inadequacies (Spiegelhalter and Riesch, 2011). Two typical types of uncertainty in this paper are discussed as follows: First, this paper conducted semi-structured interviews with EV-related stakeholders in order to set up reasonable "what-if" scenarios considering likely lottery policies in the future. However, future is not predictable and thus policy makers are suggested to examine as many scenarios (or lottery policies) as possible, so as to mitigate uncertainty in future events; Second, stochastic effects (e.g., random term) could also heavily influence model outcomes. Although each scenario in this paper was run in ten times and the average was used as the final outcome, stochastic effects could not be completely removed. Therefore, policy makers need to take the uncertainties into account.

SelfSim-EV has been found as a useful tool in this study, as it is capable of simulating both model interactions and dynamics in the system (comprising EV and its connected elements), so that it can capture some unexcepted results coming out from the interactions and dynamics. Here are some specific examples: 1) PermitCVSc1 got more PHEVs, but less electricity consumed through charging posts (see Section 4.1.4); 2) PermitBEVSc2 replaced BEVs with PHEVs, but still got more public charging posts in some central districts (see Section 4.1.2); 3) the amount of electricity consumed through public charging posts had a nonlinear relationship with the number of EVs added. These unexpected results would be particularly useful for policy makers, but have not been well captured in previous studies with traditional models (e.g., regression models and discrete choice models). However, ignoring these unexpected results in policy making would lead to, for example, improper investments in EV-related infrastructures (e.g., charging facilities) in both transport and power sectors. As results of the improper investments, 1) the usage rate of some infrastructures might be quite low, and 2) charging demand of EV drivers might not be well accommodated in some cases. These could further give rise to the low adoption and usage rate of EVs.

6. Conclusions

An agent-based spatial integrated urban model, SelfSim-EV, was used to assess the potential influence of the license plate lottery policy on the uptake of Electric Vehicles (EVs) and further its impacts on the urban environment, energy system and urban infrastructures at the micro scale. Specifically, two types of "what-if" scenario were developed to test how the methods to allocate the fixed number of vehicle purchase permits and the increase in the total number of permits could influence the EV adoption and further its connected elements. The results suggested that both of them could heavily influence the number of EV purchasers, especially Plug-in Hybrid Electric Vehicle (PHEV) purchasers: PHEVs were not attractive at all in the Reference Scenario (RefSc), but started receiving attention when the number of permits increased by 30%; furthermore, PHEVs could become more attractive if more permits were added.

Apart from the macro-level policy implications above, the EV-related stakeholders are suggested to pay more attention to those spatially explicit results and also those results coming out from the interactions and dynamics found in the system, which have not been well understood or captured in previous studies with traditional methods. From a spatial perspective, different allocation methods and permit numbers could heavily change the spatial distributions of both CV and EV owners and further the distributions of the demand for EV-related transport facilities and electricity, as well as the resulting vehicular emissions. Furthermore, SelfSim-EV simulates the EV market expansion in the context of urban evolution and thus is able to capture some unexpected results coming out from the internal interactions among consumer, manufacturer, and government agents in the vehicle market and also the external interactions between the EV market and those associated urban subsystems, including transportation, energy, environment, land use, population systems (Zhuge et al., 2019d). For instance, it was found in the PermitCVSc1 scenario that replacing CVs with PHEVs could decrease the electricity demand. Such unexpected results should be paid special attention in design or adjustment of the license plate lottery policy.

This paper evaluated two different types of license plate lottery policy within several "what-if" scenarios set up based on semi-structured interviews with EV-related stakeholders. However, due to huge uncertainty around policy making, it would be rather difficult to exactly predict the futures of EVs with few scenarios. For example, the central government of China has recently suggested that purchase restriction on EVs should be removed, which could heavily influence the license plate lottery policy. In order to deal with uncertainty in future events, policy makers are suggested to set up as many scenarios as possible, so as to better understand the possible futures of EVs and further their impacts on the connected elements.

Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Chengxiang Zhuge: Formal analysis, Writing - original draft. **Binru Wei:** Formal analysis, Writing - original draft. **Chunfu Shao:** Formal analysis, Writing - original draft. **Yuli Shan:** Formal analysis, Writing - original draft. **Chunjiao Dong:** Writing - original draft, Formal analysis.

Acknowledgement

This research was supported by the National Natural Science Foundation of China (51678044), the Fundamental Research Funds for the Central Universities (2017JBZ106), the Hong Kong Polytechnic University (1-BE2J), and the European Research Council Starting Grant for the SILCI project (Social Influence and disruptive Low Carbon Innovation, 678799). We would also thank Dr. Mike Bithell for discussing with us about the development and application of the SelfSim-EV model.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2020.111328.

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