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Consumer heterogeneity and electric vehicle diffusion in the city level: A system dynamics study based on empirical data

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ABSTRACT

The promotion of electric vehicles (EVs) in the transport sector is critical to achieve the urban sustainable goals, while the EV diffusion process varies in different cities mainly due to regional heterogeneities in consumer preferences. This research intends to reveal the EV consumer heterogeneities in the city level by applying conjoint analysis on the survey data from 1251 questionnaires collected in twelve EV promoting cities of China, and tries to simulate the possible EV diffusion process in the twelve cities by further constructing a system dynamic model. Through the study, it is found that the investigated cities could be categorized into three types from the perspective of consumer EV preference, which includes performance-driven, social-driven, and privilege policy-driven EV promoting cities. In addition, the demand heterogeneities may result in differentiated urban EV diffusion processes, which could be clustered into natural diffusion independent of policy, fast diffusion depending on appropriate policy, and lagged diffusion insensitive to policy. Based on our analysis, policy suggestions are put forward for accelerating EV diffusion in different types of cities respectively.

Keywords: Electric vehicle, City heterogeneity, Consumer preference, Policy sensitivity, Market diffusion

NOMENCLATURE

Abbreviations	
EV	Electric vehicle
ICEV	Internal combustion engine vehicle
SD	System Dynamics

1. INTRODUCTION

Mobility electrification plays a significant role in China's national strategy, which aims to reduce carbon emissions, maintain energy security, and enhance the competitiveness of automobile industry [1]. Although the Chinese government has put forward various policies for EV promotion, the EV market does not perform as well as expectation, while leaving huge fiscal burden on the central and local governments. One non-negligible reason might be that the promotion policies do not fit the local markets well in different cities [2]. For example, the time of declining subsidy policies is determined by the central government who mainly refers to the whole national situation, and the local government just followed the decision. However, some areas may be still in the initial stage of EV diffusion, where subsidy policy could be crucial and would not bring too much financial expenditure. At the same time, some cities' consumer might be less sensitive to subsidy but the policies like license/road privileges can stimulate their purchase enthusiasm in a great degree, which means the marginal effect of subsidy policy is very low and these cities could take the lead in subsidy-free. But in the one-size-fits-all mode, the characteristics of each city cannot be fully considered, which leads to the unbalance of EV diffusion or a waste of revenue.

Based on reality, it has grown up to be a pressing issue to investigate how to make suitable policies for different cities based on their own characteristics. And the first procedure is to distinguish the city heterogeneity and evaluate the matching degree of the current policy in city level. With the most appealing policies being picked up, the general diffusion pattern should also be described to show whether the EV could diffuse widely with such policy supported. By this, we

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could find the suitable policies and its diffusion degree of specific cities to give reasonable reference for urban decision makers [3].

In the literature, urban EV policy evaluation and simulation have been well studied [4,5]. Some researchers evaluate the effectiveness of EV policies by using empirical models with urban data. For example, Wang et al., using the data from 41 EV pilot cities in China, find that policies about chargers' density, license fee exemption, no driving restriction, and charging infrastructure construction are the most important factors for EV diffusion in the long term [6]. Qiu et al. assess the incentive policies at city level with 88 Chinese pilot cities and find a positive relationship between the volume of EV sales and two demand-side policies: charging discount and infrastructure construction subsidy [7]. These scholars expand the research to a more micro level and give pretty meaningful policy insights in country level. However, the action mechanism of policy and specific city's policy preference still remain to be explored. Ma et al. carried out a research about consumer preferences by questionnaire surveys, and gave the opinion that cities in different economic scales should be given heterogeneous policies [8]. But the specific city's policy preference is still to be explored. As for the diffusion simulation, several methods have been proposed, which can be divided into two types. The first type is based on probabilistic methods like Bass model [9] and logistic technology diffusion model [10]. These methods rely on available transportation data or other mature data to estimated parameters and cannot take interactions between multi-factors into consideration. Another type is based on simulation like multi-agent model [11] and system dynamics (SD) [12]. These methods pay more attention to clarify the internal mechanism of EV diffusion [13], and few researches applied cities' specific parameters to reflect the evolution pattern of EVs at different development stage, which might make the conclusions cannot link closely to a city's policy decision.

Given the current research situation and the needs of practical policy-making, this paper tries to identify city' heterogeneous preferences and give the prediction of the diffusion pattern in different policy scenarios to find the most effective way to promote EV in city level. We build the EV diffusion model on SD method, then use the conjoint analysis to estimate the parameters of specific cities based on the questionnaire that were held in 12 cities. Then, scenarios of 4 kinds of policies are simulated to determine the policy preference and diffusion pattern for each city. Finally, cluster main cities from the dimensions of consumer preference and diffusion degree. After that, we can give policies for each city according to its specific characteristics in order to support the effective diffusion of EVs.

This paper is organized as follows. Section 2 introduces the methodology used to simulate how the policy influences EV diffusion. Section 3 presents the data source and scenarios setting. Results and discussion are shown in Section 4. The conclusion and policy implication are given in Section 5.

2. THE MODEL

2.1 System dynamics model for EV diffusion

2.1.1 Model framework

The EV diffusion can be seen as the cumulative result of individual purchasing decision-making. The utility and cost are the main factors influencing consumer's choice. Consumers usually compare the EVs to the internal combustion engine vehicles (ICEVs), and they are more likely to choose the product which can bring more utility with less cost. The utility could be divided into two parts, the one is from the performance of the product, and the other one is from the additional social influences like word-of-mouth communications.

According to that, this paper constructs a conceptual model of EV diffusion based on the consumer decision-making process at the micro level, which mainly concludes purchase subsystem, demand subsystem and social impact subsystem. The core of model is the comparative analysis of the cost-utility ratio between EVs and ICEVs. In purchase decision, consumers would compare the utility and cost of ICEVs and EVs. The more sales, the more additional social influences this type of vehicle would have, which means it could have higher network externalities and better social signals. As for the mechanism of policy effect, polices could increase the performance like license/road privileges policy and decrease the cost like subsidy policy to accelerate the diffusion of EVs. The diffusion curve of EVs can be drawn by estimating the purchase probability of consumers for two types of vehicles through cost-utility ratio and combining with the prediction of vehicle ownership. By adjusting the values of the variables corresponding to the policies at all levels, the changes in the diffusion curve of EVs can directly reflect the practical effects of the policies.

The key issue for the system dynamics model is the self-feedback mechanism, which is generally described

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by the causality diagram. Based on the above conceptual model, four components, including cost, utility, social exposure, vehicle demands and sales are used to form the causal loop diagram of the EV purchase mutual feedback system, which could present the general purpose of the model and basic causal loops among

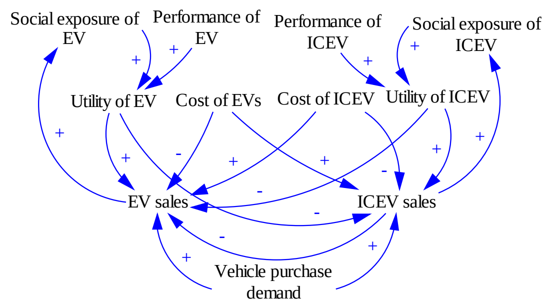

Fig 1 Key causality diagram

major model components, as shown in Fig 1.

2.1.2 Stock and flow diagram

Based on the conceptual model, the stock and flow diagram, which fit the relationship among various variables with a series of equations, could be built as shown in Fig 2. The flow stock diagram concludes three main subsystems: purchase decision subsystem, demand subsystem and social impact subsystem. Limited by space, we would only describe the key subsystems.

(1) Purchase decision subsystem

When the individuals make the vehicle purchase decision, they would compare the EVs with ICEVs. And they refer to the ratio between utility and cost to decide whether buying EV. The model of this module is shown below:

$$R_{EV} = \frac{\sum_1^n e^{U_{i\,EV}}}{\sum_1^n C_{i\,EV}}$$

$$R_{ICEV} = \frac{\sum_1^n e^{U_{i\,ICEV}}}{\sum_1^n C_{i\,ICEV}}$$

$$P_{EV} = \frac{R_{EV}}{R_{EV}+R_{ICEV}}$$

Where $U_{i\,EV}$ is the utility of EV, and it can be divided into three parts: utility from vehicle usage, utility from policy and utility from additional social influences. $C_{i\,EV}$ means the life cycle cost of EV and concludes

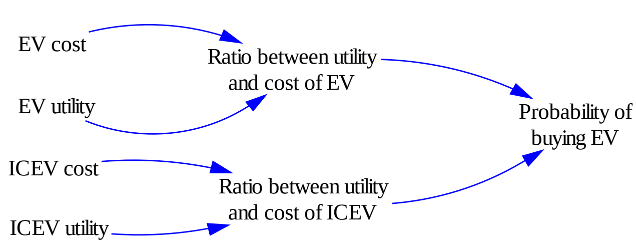

Fig 2 Flow diagram of purchase decision subsystem

purchase cost and operating cost. The R_{EV} means the ratio between the EV's utility and cost, which can be calculated through utility value to be divided by cost value. The P_{EV} means the probability of buying EV, which is determined by the utility-cost ratio of EVs and ICEVs. The ICEVs share the same modelling approach of this subsystem.

(2) Demand subsystem

The amount of EV sales is determined by the probability of buying EV and the total vehicle purchase demand. The quantity can be calculated with the first vehicle purchase and exchange-oriented purchase. The model of this module is shown below:

$$Q_d = Q_{dnew} + Q_{ICEV} + Q_{EV}$$

$$Q_{EV} = Q_d * P_{EV}$$

Where Q_d means the total purchase demand, Q_{dnew} means the new demand, and Q_{dICEV} , Q_{dEV} means the quantity of discarded ICEVs and EVs, which could indicate the demand for renewal. Q_{EV} means the demand for EVs.

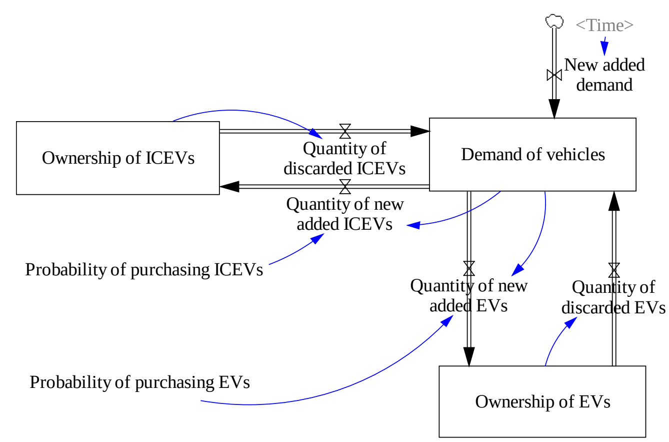

Fig 3 Flow diagram of demand subsystem

(3) Social impact subsystem

The utility of additional social influences is mainly influenced by the market size. So we choose market share as the variable and set it in the survey to determine its value in different level. In this part, we mainly introduce the calculation of market share as below:

$$Q_{EV} = \sum_1^t Q_{i\,dEV} - \sum_1^t Q_{i\,EVS}$$

$$Q_{ICEV} = \sum_1^t Q_{i\,dICEV} - \sum_1^t Q_{i\,ICEVS}$$

$$M_{EV} = \frac{Q_{EV}}{Q_{EV}+Q_{ICEV}}$$

Where Q_{EV} means the quantity of EVs, Q_{ICEV} means the quantity of ICEVs, and M_{EV} is the market share of EVs.

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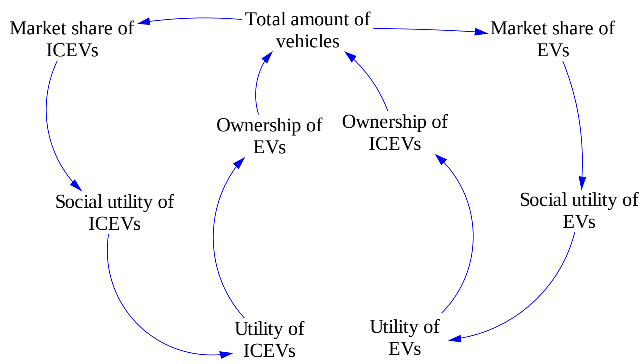

Fig 4 Flow diagram of social impact subsystem

3. SIMULATION

3.1 Data

3.1.1 Utility data

This paper uses the conjoint analysis method to estimate the parameters of the utility. The method can evaluate the relative importance of different attributes and levels to consumers. And it assumes that consumers will consider the product characteristics when making purchase decisions. When calculating the utility score, the consumer's overall score of the product portfolio is taken as the dependent variable, and the attribute level is taken as the independent variable. OLS regression analysis containing dummy variables can be used to obtain the relationship between the independent variable and the dependent variable, and the specific formula is as follows:

$$y = a + \sum_{i=1}^{m} \sum_{j=1}^{n} v_{ij} x_{ij} \tag{8}$$

Where y is total score of product portfolio, v_{ij} is utility value at level j of attribute I, and x_{ij} is dummy variable, level j of attribute i. Besides, a is a constant.

9 attributes and 25 levels are determined according to the models. The simulated product portfolios are designed with the orthogonal design method. A total of 34 outlines were generated, of which 32 were designed product combinations and 2 were holdout verified product combinations. The questionnaire was designed on the basis of the product outline card, and the interviewees were invited to rate 34 randomly assembled product portfolios according to their purchase intention. Each score is scaled by 0-100, representing the utility value brought by the product portfolio from the lowest to the highest.

We carried out the surveys in the first batch of cities from China's "Ten Cities and One Thousand Electric Vehicles" project: Beijing, Shanghai, Jinan, Hangzhou, Changsha, Hefei, Nanchang, Wuhan, Chongqing, Dalian, Shenzhen, and Qingdao. More than 100 questionnaires were distributed in each city, of which 1251 were returned. According to the results of the model, Pearson's R of the model is greater than 0.7 except Jinan. The significance test method, except Jinan city passed the test within 0.02 error probability, other city models were all within 0.01.

3.1.2 Other data

The other parameters are mainly derived from statistical bulletins.

3.2 Scenario Settings

According to previous research, this paper divides EV policies into financial incentive policies, privilege policies, and facilitating EV charging policies [16]. Based on the policy classification, the simulation scenarios are designed as follows:

Table 1: Design of simulation scenarios

Scenarios	**Simulation Mode**
Scenario 1 Cost relief policy	Diffusion under policies which aims to reduce the cost of EVs, such as exempt EV purchase tax, giving subsidy to EV charging and purchase..
Scenario 2 Privilege policy	Diffusion under policies that give EV privilege rights such as license/road privileges.
Scenario 3 Facilitating EV charging policy	Diffusion under policies that promote the construction of supporting facilities like charging station and special parking space for EVs.
Scenario 4 No policy	Diffusion under non-policy supporting.

4. RESULTS AND DISCUSSIONS

4.1 Urban consumer heterogeneity analysis

From previous study, we can get results from both conjoint analysis and system dynamics, which can be used to get different policy implications. The results of the conjoint analysis could be used to distinguish the consumer preferences in city level. According to the importance of attributes, the cities could be divided into three types: performance-driven, social-driven, and privilege policy-driven promoting cities.

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The first type is performance-driven promoting cities, which conclude Changsha, Hefei and Dalian. In these cities, consumers focus more on the vehicle performance like the top speed, charging time and endurance mileage. Based on that, we can infer that these cities' consumers have high expectation for the improvement of existing products and pay more attention to driving experience. And the subsidy policies might have side effect if the driving experience is unpleasant.

The second type is social-driven promoting cities that conclude Wuhan, Chongqing, Nanchang, Hangzhou and Qingdao. In these cities, the most important factor influencing the diffusion of EVs is the additional social influence like social comments and EV's recognition of emission reduction. The consumers in these cities place more emphasis on the feedback of products in the market, and often have a wait-and-see attitude towards new products. And the subsidy policies, which can increase EV scale rapidly, would have remarkable results.

The third type is privilege policy-driven promoting cities that concludes Beijing, Shanghai and Shenzhen. In these cities, the policies play the most important role in the diffusion of electric vehicles. If the appropriate policies were given, consumers would ignore the shortcoming of EVs and social sensation.

4.2 EV diffusion pattern in city level

The market share of EVs in 2025, under different scenarios for each city, is obtained after simulation, shown as Fig 3. It can be seen that cities have differentiated urban EV diffusion processes. Moreover, even some cities have similar consumer preferences, the diffusion might not be consistent because of the different degrees of preferences.

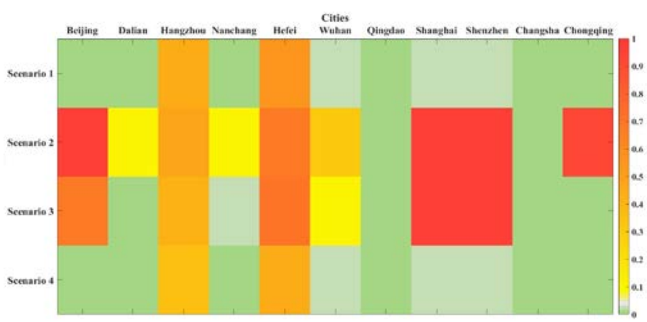

Fig 3 Urban market share of EVs in 2025

According to the "Medium and long term development plan of automobile industry" released by the Ministry of Industry and Information Technology, the market share of EVs should reach 20% in 2025. Based on the accomplishment of target goal, the cities could be divided into 3 categories: natural diffusion independent of policy, fast diffusion depending on appropriate policy, and lagged diffusion insensitive to policy.

The type of natural diffusion independent of policy concludes Hangzhou and Hefei. The simulation results show that the policies could accelerate the process, but the diffusion also could proceed naturally without policy supporting, and they can achieve the goal in natural state, as shown in Fig 4. Although the two cities' consumer have different preference, that the Hefei is performance-driven promoting city while Hangzhou is social-driven promoting city. But the utility of driving factors in different level does not vary much in Hefei. In other words, they have a high acceptance of existing EV products. Both of the cities have the same feature, that if the specific index improves, they would like EV more while the status quo does not stop their purchase behavior.

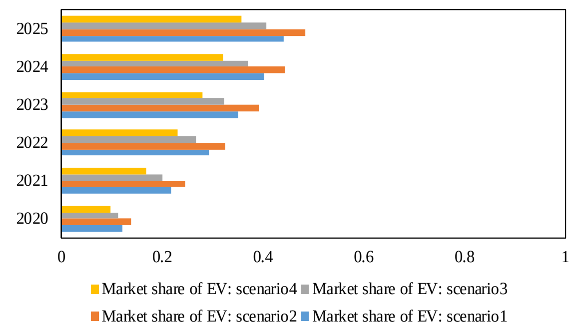

Fig 4 EV diffusion in Hangzhou

The category of fast diffusion depending on appropriate policy covers Beijing, Shanghai, Wuhan, Shanghai, Shenzhen and Chongqing. The simulation results show that EVs would diffuse widely under specific policy scenarios while keeping low degree of market acceptance in other scenarios, as shown in Fig 5. With appropriate supporting, they could exceed the promotion goals substantially. In addition, this category could be further subdivided into two types. The one type prefer both privilege policies and supporting facilities promotion policies, which concludes Beijing, Shanghai

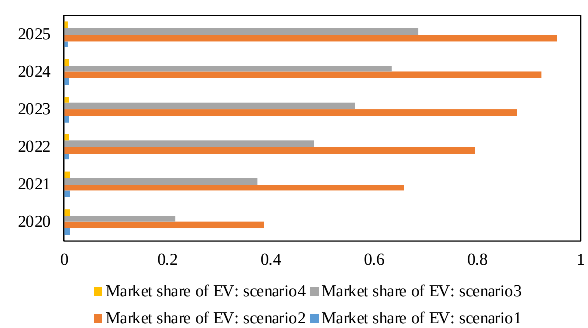

Fig 5 EV diffusion in Beijing

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and Shenzhen. The other type only prefer privilege policies, and it covers Wuhan and Chongqing.

The classification of lagged diffusion insensitive to policy concludes Nanchang, Dalian, Qingdao and Changsha. As for the results of simulation, specifically, no kinds of policies can effectively promote the diffusion of EVs in these cities, as shown in Fig 6. If only relying on policy measures, these cities will not be able to reach the target by 2025. To promote EVs, specific measures could be referred to the feature of cities. In social-driven promoting cities, the pilot policies such as electrification of official vehicles can play a better role. In performance-driven promoting cities, it is necessary to encourage the EV enterprises improve the comfortableness and safety of vehicles.

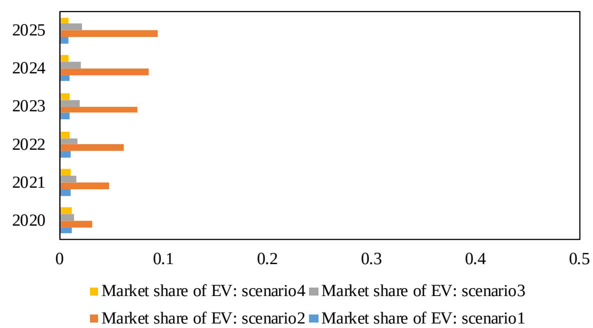

Fig 6 EV diffusion in Nanchang

5. CONCLUSIONS

This paper focuses on distinguishing the consumer heterogeneity among cities and predicting urban EV diffusion patterns under different policy scenarios. We draw the following conclusions. First, the cities do have heterogeneous preferences, which can be divided into three categories including performance-driven, social-driven, and privilege policy-driven EV promoting cities. And we infer that subsidy policy could play better role in social-driven cities. Second, cities could be clustered into natural diffusion independent of policy, fast diffusion depending on appropriate policy, and lagged diffusion insensitive to policy. And we distinguish the most effective policy for specific cities for the fast diffusion depending on appropriate policy category. For other categories, we give adaptive policy implication to support EV promotion according to their preferences and EV diffusion pattern.

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