The Impact of Service and Government-policy Attributes on Consumer Preferences for Electric Vehicles in China

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Highlights

- Data on consumer preferences for electric vehicles (EVs) is collected using stated choice experiment in different cities in China.
- Critical service factors and government policies are identified, alongside product attributes, as influencing consumer preferences for EVs in China.
- Chinese consumers have the highest willingness to pay to obtain a free license for EVs (106,144 RMB on average) and to be permitted to install a home charging post (91,039 RMB on average).
- Our findings imply that the perceived level of inconvenience is a key factor when consumers are considering switching from conventional petrol vehicles to EVs.

Abstract

This research focuses on the effects of different types of service attributes and context-based government policies, along with product attributes, on Chinese consumers' adoption of electric vehicles (EVs). Based on a stated choice experiment involving over 1,000 respondents in different cities of China, a mixed logit (MXL) model shows that typical product attributes are consistently important for potential car buyers, but that charging service has a mixed effect, depending on the level of service provision and speed. Specifically, the availability of a home charging facility has the strongest influence on consumers' choice to purchase EVs, and the service speed of public fast service stations is also significant. In relation to government policies, this study finds that in addition to government subsidy, free licensing policy for EVs is very attractive for consumers, compared to the lottery-based licensing for conventional petrol vehicles (PVs). We find that Chinese consumers have the highest willingness to pay for obtaining a free vehicle license for EVs (106,144 RMB on average) and being permitted to install a home charging post (91,039 RMB on average). Our findings imply the importance of considering consumers' perceived inconvenience associated with using EVs compared to buying and using conventional PVs. Furthermore, policy makers should consider the heterogeneous preference towards EVs when designing intervention policies in the Chinese market.

Key words: Electric Vehicles, Charging Services, Government Policies, Licensing Regulation, Mixed Logit

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1. Introduction

China is the world's largest carbon emitter and has been since 2006 (The World Bank, 2015). To address the challenges of climate change, urban air pollution and energy security, the Chinese Central Government has established a national strategy of sustainable development (National Development and Reform Commission of China, 2012). The sector of 'new-energy vehicles' (NEVs) is one of the seven strategic emerging industries to drive sustainable industrial development in China. Specifically, the current focus of the NEV sector in China is to develop two types of electric vehicles (EVs), namely plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) (National Development and Reform Commission of China, 2012, p. 15) and promote their mass marketisation (The State Council of the People's Republic of China, 2012; Wan et al., 2015).

From the perspective of systems of innovation, the transition from the oil-dependent automobile market system to a more sustainable system goes far beyond technological improvements (Williams, 2007). In the context of eco-innovations, Rennings (2000) suggests the introduction of both market pull and government regulation to address or mitigate network externality during the market penetration of innovative technologies (Hauser et al., 2006). Previous research that uses a stated preference approach to examine the likelihood of adopting alternative fuel vehicles (AFVs) typically focuses on the product or technical attributes such as the price, fuel or running cost, vehicle performance, emission level and driving range (e.g. Helveston et al., 2015; Hoen and Koetse, 2014; Larson et al., 2014; Qian and Soopramanien, 2011; Tanaka et al., 2014; Valeri and Danielis, 2015; Ziegler, 2012). Less attention has been paid to context-dependent services and government policies.

Furthermore, with the exceptions of Jensen et al. (2014) and Jensen et al. (2016), the literature in general does not empirically consider the effects of different types of service attributes. These two studies consider battery stations and charging in public areas in their stated choice experiment in Denmark and they assume that every household can install a home charging device. In this study, we examine the influences of three types of charging or refuelling services available in China: fast service stations, public or working-place charging posts, and home charging posts (Liu, 2012). We argue that it is important to consider all possible types of charging/refuelling services available to Chinese car buyers to examine the effects of these services on Chinese consumers' preferences for BEVs and PHEVs.

In relation to government policies, previous research tends to focus exclusively on policies that are targeted at promoting AFV adoption only through incentives such as providing monetary subsidy or tax exemption, free parking, and access to bus or high-occupancy vehicle (HOV) lanes (Lieven, 2015; Wang et al., 2017). We propose that a more realistic choice situation must acknowledge that potential buyers are thinking about and comparing policies that affect the utility of all the alternatives- not just AFVs. For example, major cities in China have imposed vehicle-licensing regulations such as the lottery system for allocating vehicle license plates in Beijing, Guangzhou, Shenzhen and Hangzhou and the auction process in Shanghai, which are designed to limit the uptake of private petrol cars in these cities (Chen and Zhao, 2013; Yang et al., 2014). At the same time, these local governments typically adopt less restrictive licensing policies such as the free and immediate availability of license plates for EVs (Hao et al., 2014). We argue that it is important to consider how individuals react to such policies that may influence preferences for all types of vehicles, not only the policies that aim to promote uptake of EVs.

This study provides new insights into the state of consumer preferences for EVs in China, which, since 2010, has become the world's largest car market (Qian and

Soopramanien, 2014). Most studies on consumers' adoption preferences towards EVs or AFVs are based on North American and European countries (see reviews in Dimitropoulos et al., 2013; Potoglou and Kanaroglou, 2008). However, due to the development of the Chinese car market and the importance of EVs, more recently there is a growing interest in research into whether or not Chinese car buyers will switch to EVs (Dagsvik and Liu, 2009; Helveston et al., 2015; Qian and Soopramanien, 2011). The insights from our research are particularly relevant in the context of current strategic government-policy initiatives and incentives in China, both at the national and local levels, to promote the adoption of EVs. In China, different policies are being implemented in different cities and there has not been sufficient research to evaluate which policies car buyers are most responsive to. The insights from this research can also guide private investment and/or private–public partnerships (PPPs) with regards to the provision of service infrastructure. Our research is able to demonstrate which specific types of services combined with which types of policy initiatives would be most effective in promoting consumer adoption of EVs.

This research addresses some of the limitations of previous China-based studies (e.g. Dagsvik and Liu, 2009; Helveston et al., 2015; Qian and Soopramanien, 2011) and thus we make the following specific contributions. Firstly, we include in the stated preference analysis two types of EVs that the Chinese government is strongly supporting. In comparison, Dagsvik and Liu (2009) include conventional petrol vehicles (PVs) and mention AFVs in their stated-choice scenario, and Qian and Soopramanien (2011) include BEVs, hybrid electric vehicles (HEVs) (rather than PHEVs) and PVs, because both studies were conducted before the Chinese government initiated a pilot programme to promote the EV market. Secondly, in relation to the choice of attributes in the stated choice experiment, Dagsvik and Liu (2009) do not include government policies or service attributes; Qian and Soopramanien (2011) only include the availability of charging facilities as a service attribute; Helveston et al.

(2015) only have fast-charging capability as the charging service for PHEVs and BEVs, and government policies are not directly included in their stated choice experiment.

The remainder of this paper is organised as follows. Section 2 presents the methodology of the research, including the design of the stated choice experiment, the data collection process, the description of sample characteristics, and the specification of the discrete-choice model. Section 3 presents the empirical results based on the mixed logit (MXL) model, the corresponding willingness to pay (WTP) and a simulation for key service and policy attributes. Section 4 summarises the specific contributions of this research and discusses its policy implications.

2. Method

2.1. Stated choice experiment design

According to the China Association of Automobile Manufacturers (2016), the market share of EVs was only 1.35% in the 2015 Chinese automobile market and EVs only accounted for 0.98% of the market share in the passenger car sector. These figures demonstrate that the diffusion of EVs in China is still in its infancy and thus we apply the stated choice experiment approach to analyse the stated preference (SP), which is typically employed when a market is at this stage of development.

2.1.1. Attributes and levels

In this study, we consider three alternatives in the stated choice experiment: PVs, PHEVs and BEVs, in specific consideration of the fact that the latter two types of vehicles receive substantial government support in China. We include a range of attributes related to products, services and government policy in the experiment. The inclusion of these attributes in the experiment is based on a thorough review of the literature, an interview with a market expert from J.D. Power China, and our pilot study, and takes into consideration their importance in the context of China.

Firstly, we consider the vehicle purchase price, annual running cost, and vehicle driving range as three main product attributes because they are the three most common product-related attributes included in choice experiments when investigating consumer preferences for AFVs (Hoen and Koetse, 2014). We conducted a pilot study to test other product-related attributes, such as acceleration speed and emission level, but we found that they are not considered to be important by Chinese consumers at the current stage of EV adoption. Following the well-known pivoting technique in the stated choice experiment (Hensher et al., 2015) and its applications in the literature (Hackbarth and Madlener, 2013; Qian and Soopramanien, 2011), respondents first chose the price range of cars they would consider buying. The choice scenarios that were subsequently presented were more customised to better reflect each respondent's price preference (Hensher et al., 2015)[1]. Based on the chosen price range of a PV by each participant, the prices of PHEVs and BEVs can vary at three different levels (i.e. PHEVs were assumed to be priced 20%, 40% and 60% higher than similar-sized PVs, and BEVs were assumed to be priced 30%, 50% and 70% higher than similar-sized PVs). The annual running cost for PVs was based on the market average running cost of each class of PVs (e.g. 20,000 RMB per year for a small-sized vehicle priced less than 100,000 RMB). The running cost for PHEVs was assumed to be 40%, 50% or 60% of the running cost of similar-sized PVs, and the running cost of BEVs was assumed to be 10%, 25% or 40% of the running cost of similar-sized PVs. In addition to the higher purchase

[1] In order to investigate whether respondents in different intended price ranges have different preferences for the choice attributes, we estimated a MNL model that accounts for the interactions between choice attributes and price ranges. The insignificant coefficients of the interaction terms suggest no evidence to separate different groups of respondents. In addition, we control for the four price ranges (i.e. lower than 100k RMB, between 100k and 200k RMB, between 200k and 300k RMB and over 300k RMB) using dummy variables in the model, where the intended price over 300k RMB is the reference category, by interacting them with the alternative specific constants (ASCs) of both BEVs and PHEVs. We thank anonymous reviewers for their suggestions.

price of EVs, the limited driving range of these cars has been found to be another significant barrier to EV adoption (Franke and Krems, 2013). In our experiment, the driving range of PVs was fixed at 600 kilometres, while that of the BEVs could vary between 80, 150 and 200 kilometres fully driven by electricity. The driving range of PHEVs consists of a fixed range of 600 kilometres driven by petrol, plus a variation part driven by electricity, which can be 50, 70 or 100 kilometres. Dimitropoulos et al. (2013) propose that, compared to the commonly used linear-in-range utility specification, it is more reasonable to expect that the marginal effect of the increase in the driving range for vehicles with shorter range would be higher than the marginal effect for vehicles with longer range. Specifically, following Jensen et al. (2013), we differentiate the marginal effects of adding one extra kilometre of driving ranges between BEVs and PVs/PHEVs, where the former have much shorter driving ranges than the latter[2].

Secondly, we differentiate service attributes based on three types of charging facilities available in China: public fast service stations, workplace/public slow changing posts and home slow charging posts (Liu, 2012). Of these three service facilities, the fast service stations provide fast battery charging or battery-swapping services. The public or workplace charging posts and home charging posts typically use slow charging technology, which requires 6 to 10 hours for a full recharge (Liu, 2012). Furthermore, the service capability for each type of charging facility is presented from two aspects: geographical coverage and service speed (Jensen et al., 2014). We follow the literature to define the availability of public fast service stations as the percentage of existing gas stations (Tanaka et al., 2014) and the coverage of workplace/public charging posts as the percentage of parking spaces (Qian and

[2] We appreciate the valuable comment from one anonymous reviewer to account for the possibility of nonlinear effect of driving range. We actually tried three different specifications of non-linear range (including short-long range, logarithmic transformation of range and quadratic term of range) in addition to the linear range. We find the models with short-long range, logarithmic transformation of range or linear range can be selected given their significant coefficients. However, it is important to note our main conclusions remain robust in this paper, regardless of the change of range specification.

Soopramanien, 2011). For home charging facilities, many Chinese households do not typically have a dedicated parking space at home or face restrictions to install residential charging posts (Wang, 2015). So, we introduce a dummy variable to examine the effect of the possibility of having a home charging post. In relation to the service speed at fast service stations, we assume that PVs can be refuelled at a fixed speed of 5 minutes at typical gas stations, whilst PHEVs can be fully charged after 10, 20 or 30 minutes and BEVs can be fully refuelled in 5 minutes with a battery-swapping process or can be fully charged in 15 or 30 minutes for fast charging. We also assume that home charging posts and workplace/public slow charging posts will have the same but slow charging speed, which is assumed to vary at three levels for each type of EVs (i.e. 4 hours, 6 hours and 8 hours for PHEVs and 6 hours, 8 hours and 10 hours for BEVs).

Thirdly, we include two types of public policies in the stated choice experiment. We first consider the effect of government subsidy, which is a common policy used in many markets to encourage the purchase of EVs. The government subsidy in China is designed to be largely proportionate to the vehicle's battery capacity (Helveston et al., 2015), and vehicle battery is the principal source of the price premium of the PHEVs and BEVs compared to the PVs (Delucchi and Lipman, 2001), so we assume the government subsidy for each PHEV purchase will vary at three levels: 0%, 10% or 20% of the vehicle purchase price, and the subsidy for the BEV could be 10%, 20% or 30% of the corresponding BEV's purchase price. The second policy is the vehicle-licensing regulation, which is imposed in several big cities in China (e.g. Beijing, Shanghai, Shenzhen, Guangzhou and Tianjin). The lottery-based licensing process is adopted by the majority of these cities to regulate the massive growth of PVs, while PHEVs and BEVs are either exempt from this lottery process or granted a higher chance to be licensed (Xing et al., 2016). Considering these licensing practices, we assume in our experiment that licensing PVs is enforced through the lottery process, while both PHEVs and BEVs may be subject to two systems (e.g. either the lottery process or free and immediate licensing). Table 1 describes all the attributes and their levels in the stated choice experiment in this study.

Insert Table 1 here.

2.1.2. Experiment design procedure

For the experiment design, we adopt the D-efficient design, which minimises the D-error of the asymptotic variance–covariance (AVC) matrix for the design (Rose and Bliemer, 2009). Specifically, there are six key stages in our experiment design as follows: (see also Table 2)

(1). Following Rose and Bliemer (2009), we set our initial proposal of the attributes and levels based on expert interviews and literature review as well as our knowledge about the specific market. Since we did not have priors about the design at this stage, we generated an orthogonal design with the help of Ngene.

(2). We launched a pre-pilot survey of 60 individuals.

(3). With the pre-pilot survey, we estimated a multinomial logit (MNL) model. We used this model to set new attributes, levels and priors. With such priors we generated a new efficient D-design using a purposely written programme in Visual Basic for Applications (VBA) in Excel[3] following the step-by-step guide provided in Appendix A of Rose et al. (2008).

(4). We launched a pilot survey of 54 individuals.

(5). With the new pilot survey, we updated our design in terms of the attributes, levels and priors again using the same VBA–Excel framework.

(6). We established the final design, which is used for the data collection.

[3] The reason to use VBA-Excel framework at this step is that our D-efficient design is quite complex and by using VBA-Excel framework we can better control the entire process, even if there are any errors that may stop the Ngene programme. In the VBA algorithm, we just added few lines explaining that, in case of errors, the program should go to the initial randomization and keep running until reaching the best design – which is the one with the minimum D-error.

Insert Table 2 here.

We consider 24 choice scenarios from the stated choice experiment design for the following reasons. Firstly, according to Rose and Bliemer (2009), the minimal number of choice scenarios from the design ‘should be equal to or greater than the number of (design-related) parameters, not including constants, plus one’ (p. 589). In our study, we have a total of 10 attributes in the design. Since we wanted to make sure that our experiment choice scenarios could accommodate the possible heterogeneity, for example, assuming normally distributed random coefficient of every attribute, there would be 20 design-related parameters to estimate. Therefore, the minimum number of choice scenarios should be 21. Secondly, we begin with a balanced design with an equal number of attribute levels for every attribute. Given that we have both two-level and three-level attributes, the number of choice scenarios should be divisible by both two and three. See the similar example explanation in Rose and Bliemer (2009, p. 590). Therefore, to maintain the balance of the design level, we decided to use 24 choice scenarios. It is widely acknowledged that 24 choice scenarios are too many for a single respondent (Caussade et al., 2005), so we used random blocking to assign six choice scenarios to each respondent. Figure 1 depicts a sample choice scenario. It is worth noting that, in order to reduce the cognitive effort for participants in interpreting the attributes, we employed images in addition to text description to present the values of non-monetary attributes. The images of the three types of vehicles were adapted from Schuitema et al. (2013).

Insert Figure 1 here.

2.2. Data collection

The stated choice experiment was implemented through a nationwide online survey in China. China is a highly heterogeneous market due to its population and geographical size. A McKinsey study about local strategy in emerging markets identifies 22 urban clusters in

China based on demographic, geographic, economic and consumer characteristics, where every cluster can be considered as a relatively homogeneous sub-market (Atsmon et al., 2011). Using similar regional clusters, a follow-up study by McKinsey identifies 25 distinct automobile-market clusters comprising 75% of the Chinese automotive market in 2011, and the study predicts that most of the growth in the Chinese car market during the period 2011–2020 will occur in these regions (Wang et al., 2012). We use these regional clusters identified by these two McKinsey studies as our sampling frame. We recruited a survey assistant team of 52 university students whose hometowns and cities are located in 24 automobile-market clusters.

We first conducted pilot surveys in December 2014 and January 2015 to improve the questionnaire and the experiment design, and to test the online survey platform. Before the start of the data collection, we provided specific training to all survey assistants on the purpose of the research, how to recruit participants in their home town and how to communicate with potential respondents. The nationwide survey was implemented during the winter holiday of Chinese universities in January and February 2015. During this period, our survey assistants returned to their home cities and collected the data from their acquaintances in the respective urban clusters. The survey assistants provided the online survey link to participants, with all the necessary explanations on the objective of our survey and research. Whenever the participants had difficulties in accessing the internet, our survey assistants were able to provide their own internet-accessible mobile devices so that the participants were able to complete the online survey, thus reducing the potential sampling bias to the internet users. It is worth noting that, although we applied a convenience sampling approach within each cluster to recruit survey respondents, we collected data from a wide range of urban areas in China (see the tier of residential city variable described in Table 3), and importantly the coverage of our survey exercise is wider and more diverse than previous studies that typically focus on only large cities in China (e.g. Dagsvik and Liu, 2009; Helveston et al., 2015). We had 2,361 visits to our online survey, and we collected 1,364 submitted responses, providing a completion rate of 57.77%. After deleting some responses that had missing data on key questions, we had 1,076 usable cases for the discrete choice modelling analysis.

Insert Table 3 here

Table 3 presents a summary of demographic characteristics of our sample. Similar to the research of Helveston et al. (2015), our sample has slightly more male than female participants. Approximately 95% of participants are aged between 18 and 50 years old, and most are well educated with university degrees. More than 40% of our survey participants have a mid-level annual household income (between 100,000 and 200,000 RMB in 2014), and 27% fall into the low-income group (less than 100,000 RMB in 2014). As expected, most participants have three members in their immediate family, but four-member families accounted for 20% of our sample. In recruiting households from 24 automobile-market clusters in China, we collected data from different tiers of cities within these clusters (see the official classification of city sizes from The State Council of China, 2014): 8.92% of our sample from 6 Tier 1 cities (those with a population of more than 10 million people) located in 5 clusters, 15.15% of the sample from 6 Tier 2 cities (those with a population between 5 million and 10 million people) in 6 clusters, 25.19% of the sample from 12 Tier 3 cities (those with a population between 3 million and 5 million people) in 12 clusters, 21.65% of the sample from 8 Tier 4 cities (those with a population between 1 million and 3 million people) in 7 clusters, and 29.09% of our sample from 10 Tier 5 and smaller cities (those with a population of less than 1 million people) in 9 clusters. Our sample had 58% of households owning one car, and 24% households owning two and more cars. Compared to the average car-ownership level in Chinese urban areas in 2014, we have more car owners in our sample, but this may better fit the research purpose of understanding the preferences of potential EV adopters because prior literature has demonstrated that compared with the first-car purchase intentions of non-car owners, car owners are more likely to prefer alternatively fuelled vehicles than conventional PVs when buying their second or third car (Lieven et al., 2011; Qian and Soopramanien, 2011). However, we acknowledge this issue and reweigh our data in the model estimation based on China's national average car-ownership level in 2014 to address the generalisability of our results.

2.3. Model specification

Given the stated choice data, we formulate a panel random-utility model (Hensher et al., 2015; Train, 2009), assuming that individual *n* will choose alternative *i* from the choice set in choice scenario *t* if *i* provides the greatest utility U_{nit}, which consists of an observable part V_{nit} and an error term ε_{nit}

$$U_{nit} = V_{nit} + \varepsilon_{nit}. \tag{1}$$

The multinomial logit (MNL) model assumes that the observed utility V_{nit} is deterministic (i.e. not stochastic) and the error term ε_{nit} is independent and identically distributed (IID) with type I Extreme Value distribution. Thus the choice probability of MNL model is:

$$P_{nit} = \frac{\exp(V_{nit})}{\sum_j \exp(V_{njt})} \tag{2}$$

As an extension of the MNL model, an MXL model relaxes the assumption of independence from irrelevant alternatives (IIA) by allowing for random taste variation among individuals and unrestricted substitution patterns between alternatives (McFadden and Train, 2000; Train, 2009). Specifically, we adopt the error component logit (ECL) model, as a form of MXL model[4], and assume that each utility function has its alternative specific error component. Thus, following Greene and Hensher (2007), we rewrite the utility function in Eq(1) as

$$U_{nit} = \delta_i + \beta^{'} x_{nit} + \gamma_i y_n + W_{ni} + \varepsilon_{nit} \tag{3}$$

where δ_i is the alternative specific constant (ASC) of each alternative; x_{nit} is the alternative attribute related to our study's products, services and government policies observed by individual *n* for alternative *i* in choice scenario *t*, and β represents the vector of the mean coefficients for the observed attributes; y_n is the vector of choice-invariant individual's socioeconomic characteristics; W_{ni} is the alternative-specific error component that is normally distributed with zero mean and standard deviation to be estimated. Following Tanaka et al. (2014), we assume that the error component for each alternative is the random portion of the observed utility. More specifically, the utility function in Eq(3) can be further expanded into a more detailed equation as follows:

$$U_{nit} = \delta_i + \beta_1' \mathrm{PROD}_{nit} + \beta_2' \mathrm{SERV}_{nit} + \beta_3' \mathrm{GOV}_{nit} + \gamma_{1i}' Z_n + \gamma_{2i}' PI_n + W_{ni} + \varepsilon_{nit}$$

$$\begin{array}{ll}
\text{ASC:} & = \delta_i \\
\text{Product attributes:} & + \beta_1^{Price}\mathrm{Price}_{nit} + \beta_1^{RCost}\mathrm{RunCost}_{nit} + \begin{cases} \beta_1^{SR}\mathrm{Range}_{nit} & \text{for } i = \text{BEVs} \\ \beta_1^{LR}\mathrm{Range}_{nit} & \text{for } i \neq \text{BEVs} \end{cases} \\
\text{Service coverages:} & + \beta_2^{FastCOV}\mathrm{FastCOV}_{nit} + \beta_2^{SlowCOV}\mathrm{SlowCOV}_{nit} + \beta_2^{HomePost}\mathrm{HomePost}_{nit} \\
\text{Service speeds:} & + \beta_2^{FastSpeed}\mathrm{FastSpeed}_{nit} + \beta_2^{SlowSpeed}\mathrm{SlowSpeed}_{nit} \\
\text{Government policies:} & + \beta_3^{Subsidy}\mathrm{Subsidy}_{nit} + \beta_3^{Licensing}\mathrm{Licensing}_{nit} \\
\text{Socioeconomic factors:} & + \gamma_{1i}' Z_n \\
\text{Intended price ranges:} & + \gamma_{2i}' PI_n \\
\text{Error component:} & + W_{ni} \\
\text{IID Error term:} & + \varepsilon_{nit},
\end{array} \tag{4}$$

[4] We note that there are two different specifications of MXL model and Train (2009) highlights that "error-component and random-coefficient specifications are formally equivalent" (p.140). We have also tried random coefficients specifications of the MXL model, but it turns out that ECL specification has the better model performance (measured by log-likelihood at convergence) with fewer estimated coefficients.

where β_1^{SR} captures the marginal effect of adding an extra kilometre to the range of BEVs, which have driving range no longer than 200 kilometres in our study, and β_1^{LR} is the coefficient for the range of PVs and PHEVs that have driving range of at least 600 kilometres.

To investigate market-level heterogeneity, we estimate the MNL and MXL model in ECL specification using NLogit v5.0 (Greene, 2012). When estimating the MXL model, we use the standard Halton sequence, which is 'the most common form of intelligence draw used in the model estimation' (Hensher et al., 2005, p. 626). Specifically, we employ 500 Halton random draws[5] in the maximum-simulated likelihood estimation process for the MXL model.

3. Results

We first start by conducting a thorough analysis of the interaction effects between the choice attributes and socioeconomic factors by estimating different MNL models. We find that the tier of cities variable is the factor that produces the most systematic taste variation[6] and this factor is also of practical importance for public policy intervention. Therefore, this suggests that we should employ a model that not only captures the (unobserved) preference heterogeneity via the random error components in the ECL specification, but also accounts for the potential systematic taste variations by including interactions of socioeconomic factors with stated choice experiment attributes, similar to the modelling approach of Grisolía et al. (2015) and Ortúzar and Willumsen (2011, p. 279).

3.1. Model estimation results

Table 4 presents the estimation results of the MXL model with error component specification. The goodness-of-fit of the model is assessed using the log-likelihood (LL) function at

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[5] We notice that the literature varies significantly on the number of random draws when estimating MXL model, ranging from 100 Halton draws (Tanaka, et al., 2014) to 2000 Halton draws (Hoen and Koetse, 2014). We thank the suggestion from one reviewer on this point.

[6] We thank one of the anonymous reviewers for the suggestion on accounting for systematic heterogeneity.

convergence. Compared with the LL value of the corresponding MNL (-2335.620), the MXL model has a much better LL value at convergence (-1777.793) and its McFadden ρ^2 index[7] is 0.274. An LL ratio test can also be conducted to examine the performance advantage of the MXL model over the MNL model. The test statistic is $-2 \times (LL_{MNL} - LL_{MXL})$, following chi-squared distribution with the degrees of freedom equalling the number of additional parameters in the MXL model (see Hensher et al., 2005; Ortúzar and Willumsen, 2011). The LL ratio test clearly demonstrates that the MXL model outperforms the MNL model, indicated by the chi-squared statistic of 1115.654 with three degrees of freedom ($p < 0.001$). The ECL specification of the MXL model also shows that every error component has a statistically significant standard deviation, where the differences in the variance of every error component imply that there is (unobserved) preference heterogeneity across three alternatives (Tanaka et al., 2014; Train, 2009). We therefore focus on the MXL model when we discuss our results later on.

Insert Table 4 here

In our model, by using PVs as the reference alternative, the ASCs for both BEVs and PHEVs have positive signs and the specific ASC of PHEVs is statistically significant, which implies that if there were no differences in attributes across these three alternatives, the respondents would not be opposed to EV adoption and would even be supportive of PHEVs in particular.

The product attributes consist of vehicle purchase price, annual running costs, and vehicle driving range after full charging or refuelling. The MXL model shows that the estimated coefficients of these product attributes are significant with the expected signs. More specifically, Chinese consumers generally perceive the annual running cost to be more important than the vehicle purchase price, given that the estimated coefficient of the former

[7] McFadden ρ^2 index is calculated as $1 - \frac{\text{LL value of the MXL model}}{\text{LL value of constant−only model}}$ (Ortúzar and Willumsen, 2011, p. 282).

attribute is much bigger that of the latter coefficient. This is not surprising in a market where the alternatives are defined by attributes related to their operational features and we note that our findings corroborate the findings in previous literature that Chinese consumers are willing to pay nearly double premium for the running cost reduction than the U.S. counterpart (Helveston et al., 2015). That might be related to the long-term orientation of the Chinese culture (Hofstede, 2001; Hofstede and Bond, 1988), which plays an important role in the Chinese consumers' intention for adopting EVs (Qian and Yin, 2017). Compared to the high cost of buying any type of car, they are much more responsive to the long term saving on the running cost that will increase their utility from the daily use. Driving range is defined as the kilometres for driving without the need for recharging or refuelling, which represents the contribution to the utility of each type of vehicles per kilometre. When differentiating the marginal effect for BEVs that have a much shorter driving range than PVs/PHEVs, we find that the estimated coefficient of the driving range for BEVs is statistically significant at 10% level with an expected positive sign. But this coefficient is significant at 5% level based on the one-sided test. In comparison, the coefficient of the driving range for PVs and PHEVs is insignificant. This implies that Chinese consumers might buy BEVs but only if they have longer driving range because of the driving range anxiety attached to BEVs compared to PVs and PHEVs. This finding on the heterogeneous valuation of the driving ranges of different types of vehicles is broadly consistent with the findings in the recent literature (e.g. Hackbarth and Madlener, 2013; Hoen and Koetse, 2014; Jensen et al., 2013) .

In relation to the effect of service attributes, our model includes service speeds for both public fast service stations and slow charging posts, and coverage or availability of three types of charging/refuelling service provisions (which are the coverage of public fast service stations, the coverage of workplace/public slow charging posts, and the permission to install home slow charging posts). For the two attributes related to service speed, both coefficients have negative signs, and the coefficient of the service speed in a fast service station is significant at the 5% level, whereas the charging speed provided by slow charging posts is insignificant.

Furthermore, we find a similar systematic taste variation effect for these two factors of service speed across different sizes of cities in China. That is, those who live in Tier 1 cities are more concerned about both fast and slow service speed than those in other cities, as indicated by the negative coefficients of the interaction effects between each type of service speed and the dummy variable of Tier 1 cities. This implies that time is more valued by consumers in Tier 1 cities where the pace of life is faster and these consumers feel they are wasting time when they are waiting for their cars to be charged.

Amongst the three attributes related to the availability of service provision, only the permission to install a home slow charging post is significant and its effect is considerably larger than those of the other two insignificant variables. This implies that Chinese consumers generally do not find the availability of public service facilities important. Instead, they prefer the perceived convenience of home charging posts that they can use exclusively over the inconvenience of having to find public charging facilities. This corroborates with the findings of Helveston et al. (2015) that Chinese consumers are more likely to adopt PHEVs and BEVs if they can charge the batteries for these cars at home. This is reasonable considering China's high population density and residential conditions. Most Chinese urban households live in apartments in multi-family buildings, so that many households do not have the space or permission from property-management firms to install home charging posts.[8] The wide availability of home charging is a more realistic scenario in developed markets whose households reside in private homes and can benefit from this type of service (Jensen et al.,

[8] See a domestic news item in China on the difficulty of installing home charging posts: 'Why Do Property Management Firms Forbid Installing Home Charging Posts' (http://house.people.com.cn/n1/2016/0111/c164220-28035343.html).

2014). Compared with home charging posts that EV owners can use exclusively, public/workplace charging facilities are shared with other EV users living in the neighbourhood or working in the organisations. This means that the public/workplace charging facilities may be occupied, which forces users to wait in queue or go to other service stations or charging places. This implies a risk associated with the perceived service scarcity (Lamberton and Rose, 2012), which reduces the value of public service stations and public/workplace charging posts in the mind of potential users.

We find that the policy attributes, including both free licensing and government subsidy, are statistically significant with positive signs. The government subsidy has a significant coefficient of 0.061, which is in line with Qian and Soopramanien (2015) finding on the effect of government cash subsidies on car owners. Free vehicle licensing is a policy attribute unique to the context of China and thus has not been tested in other studies and markets. Our model shows that free vehicle licensing produces the biggest estimated coefficient − 0.587 − among all product, service and policy attributes involved in this study. This provides an important policy insight into the effectiveness of the different incentive policies of the EV market.

To study the preference heterogeneity for non-conventional vehicles due to other variables, we control for a range of socioeconomic characteristics in our model, including individual age and gender, as well as the income and family size of the household, to interact with the ASCs of BEVs or PHEVs, with the reference to PVs. First, considering consumers aged 51 years and older as the reference category, the MXL model shows a U-shape non-linear effect on age. Specifically, we find that middle-aged Chinese consumers (aged between 41 and 50 years) are least likely to adopt both types of EVs, followed by consumers aged between 31 and 40 years and then between 18 and 30 years. In comparison, many studies in the literature are concerned with the linear effect of age and find that younger consumers prefer EVs or clean vehicles more than older consumers (see Carley et al., 2013; Potoglou and Kanaroglou, 2007; Qian and Soopramanien, 2011). Our model also finds that female consumers are more likely to adopt both types of EVs than male consumers are, which corroborates the findings of Qian and Soopramanien (2011) but differs from those of Tanaka et al. (2014).

Amongst the household-level characteristics, household income generally has a negative effect on the adoption of PHEVs and BEVs (with household income below 100,000 RMB in 2014 as the reference category), which corroborates Helveston et al. (2015) who find that the high income group in the U.S. is more opposed to the full range of electrified vehicles, including both PHEVs and BEVs, compared to the low income group. Initially, this negative effect seems counterintuitive; however, this relationship must be interpreted in the context of the Chinese car market in consideration of how Chinese consumers perceive the EV brands available in the market. Most (or the best-selling) EVs in China in 2015 (or earlier) were made by domestic car makers, addressing the needs of the lower end market,[9] and thus could be perceived to be of lower quality and have a poorer brand image than international competitors. This may explain why higher income groups are less likely to choose EVs. Other results indicate that family size is significant at 10% level with the positive sign for the choice probability of BEVs, which is in line with the finding from Plötz et al. (2014) that multi-person households are more likely to be EV users.

To control for any potential endogeneity effect of the price ranges which are presented to respondents in the experiment, we include the interaction of intended price ranges with ASCs in the utility function, with reference to the highest intended vehicle price range (over 300,000 RMB). The interaction effects between price ranges and ASCs in the MXL model

[9] The New Energy Vehicle Sales Ranking in 2015 Released; Insider: they are all three-low products (low-development cost, low technology, low price) http://finance.sina.com.cn/roll/2016-01-24/doc-ifxnuvxc1771094.shtml (original news in Chinese).

generally shows that, compared to those who intend to buy vehicles in the highest price range (as the reference category), consumers who intend to buy vehicles in the lowest price range are more likely to choose BEVs, as indicated by the positive and significant interaction term. This corroborates our earlier findings on the impact of household income and provides further evidence that consumers who plan to buy less expensive cars are more likely to adopt EVs.

3.2. Willingness to pay

Based on the estimated coefficients of key attributes (including annual running cost, driving range of BEVs, fast service speed, permission to install home charging post, and free vehicle licensing) and vehicle purchase price, we calculate the WTP as the ratio of the coefficients of the attributes over the estimated parameter of vehicle purchase price. Furthermore, we also calculate the 95% confidence intervals of WTPs using the simulation-based bootstrapping percentile method (Gatta et al., 2015)[10]. In general, we obtain wide confidence intervals of WTPs, which corroborate the prior studies in the literature (Helveston et al., 2015; Jensen et al., 2013) and generally suggest the heterogeneity on WTPs for the key attributes related to EV adoption. The point estimates of the WTPs for these key attributes and the corresponding confidence intervals are shown Table 5.

Insert Table 5 here.

The point estimate of the WTP for reduced annual running cost is 10 RMB on vehicle purchase price per RMB saving of annual running cost. This is largely aligned with the results in the literature on the WTP for running or operational cost saving. For example, Helveston et al. (2015) find that Chinese consumers are willing to pay US$3,000 for

[10] We have also tried other methods for calculating WTP confidence interval, such as the asymptotic t-test method (Armstrong et al., 2001), which yield similar results to what is reported in the paper.

US$0.01/mile decrease in operating costs. Given that the Chinese consumers typically drive their private cars around 15,000 kilometres annually (GfK Group, 2014), their estimated WTP is US$32 per $1 saving on annual operational cost, which is higher than our estimate. Hackbarth and Madlener (2016) estimate the average WTP of €1,056 for €0.01/km fuel cost saving, which is equivalent to €7 per €1 saving on fuel cost reduction. We also notice that the confidence interval of annual running cost is asymmetric and has a relatively large upper bound, which corroborates the patterns of confidence intervals found in Jensen et al. (2013).

The point estimate of WTP for driving range of BEVs is about 587 RMB (approximately US$94) per additional kilometer and this falls in the range of the point estimate WTP for driving range in Jensen et al. (2013) for €3.3-134 (about US$3.8-154) per kilometer and Hackbarth and Madlener (2016) for €12-125 (about US$14-144) per kilometer. Given that the coefficient of BEVs' driving range is significant at 10% level based on the two-sided test, its 95% confidence interval of WTP is between -19 RMB (approximately US$-3, which is close to zero compared to the large value in upper bound) and 1,689 RMB (approximately US$ 270) in our study. This is largely in line with Jensen et al. (2013)'s confidence interval [€0.2, €193], equivalent to [US$0.24, US$232] for one kilometer increase in driving range.

Amongst the two key service attributes, the WTP point estimate for fast service speed is 2,424 RMB (approximately US$387) to save one minute using a fast service station, which is larger than the WTP of €182 (approximately US$220) per minute saving for fast refuelling of fuel cell vehicle in the Netherlands (Hoen and Koetse, 2014) and €194 (about US$233) per minute saving for fast battery charging in Germany (Hackbarth and Madlener, 2016). Also, the 95% confidence interval of the WTP for fast charging speed is generally higher than the interval from Hackbarth and Madlener (2016). This difference in WTP for fast charging speed can be explained by the fact that consumers in Eastern cultures tend to be more impatient when they are faced with the threat of a delayed service, because “Easterners are more prevention focused and they emphasize on ensuring that undesirable outcomes do not occur” (Chen et al., 2005, p. 294) . Specifically, in our research context, Chinese consumers are impatient for the fast charging service, as its service delay or failure is a prevention loss and thus they want to have their vehicles fully charged as soon as possible. On the other hand, this is a WTP for saving one minute in every fast refuelling/recharging service during the whole period of owning and using this vehicle, which might take several years[11].

As for the other key service attributes, we find a significant point estimate WTP of 91,039 RMB (US$14,556) for the permission to install a home charging post, and the corresponding 95% confidence interval is between 35,518 RMB (US$ 5,679) and 215,910 RMB (US$ 34,521). This is one of the largest WTP values amongst all service and policy attributes that we consider, demonstrating the significant importance for consumers of having access to home charging facilities. The high WTP for home charging can be explained by the difficulties of installing home charging posts in China. Firstly, most urban households in China live in multi-family buildings instead of single family houses in the West and importantly not every household has its own dedicated parking space in their living compound. Secondly, even if a household owns the parking space, they will still need the approval or agreement from the property management firm and their neighbours before installing a home charging post. It is very likely that the property management firms would reject residents’ requests to install such facilities for the reasons concerning electricity safety or insufficient electricity capacity[12].

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[11] According to Mckinsey, most Chinese households replace their cars every six to eight years (Sha et al., 2013, p.6).

[12] See related news report in China: “Why Do Property Management Firm Forbid Installing Home Charging Post”, People Daily, 11th January 2016, http://paper.people.com.cn/rmrb/html/2016-01/11/nw.D110000renmrb_20160111_1-10.htm

For the policy attributes, free vehicle licensing has a point estimate WTP of 106,144RMB (approximately US$16,970) when potential car buyers are comparing to the alternative of waiting for the lottery process of licensing their vehicles. The corresponding 95% confidence interval of this WTP has a lower limit of 60,658 RMB (US$ 9,698) and an upper limit of 230,666 RMB (US$ 36,880). This policy produces the highest WTP in our study and, more importantly, it is a unique non-monetary incentive policy that has been implemented in some big cities in China along with the restrictive licensing policy for conventional petrol cars (Hao et al., 2014). As far as we are aware, this study represents the first attempt to quantify the potential effect this type of vehicle-licensing policy on a nationwide level in China. Our calculation of WTP is generally aligned with the recent finding in the literature that Beijing and Shanghai residents are willing to give up the subsidy of 102,000 RMB and 85,000 RMB respectively to get a vehicle license for the EVs immediately (Yang et al., 2017). The importance of this policy also has its advantages over other government policy measures, in that it neither uses government budget nor interferes with other road users as the side effect of other policies such as the free use of bus lanes[13].

3.3. Market share simulation on key attributes

We also conducted simulation exercises on the key service and policy attributes to evaluate the potential market share changes for each alternative with respect to a change in one or multiple attributes. Table 6 shows the definitions of different simulation scenarios and the corresponding market shares of every alternative. The simulation exercise is similar to Hackbarth and Madlener (2013). The base scenario in our simulation is defined with the following attributes: fast service needs 30 minutes and there is no home charging, no free license and no government subsidy for two types of EVs. Scenarios 1 to 4 show the results

[13] We thank one anonymous reviewer for suggesting this important implication.

for policy changes in the level of one attribute respectively and scenario 5 has all attribute changes simultaneously. The market shares are calculated based on the socioeconomic characteristics in our sample and other observed attributes in our stated choice experiment.

Insert Table 6 here

Table 6 shows that the provision of either home charging or free vehicle license can help increase the market shares of EVs by reducing the market share of PVs by 5% (from 37% in the base scenario to about 32% in both scenario 2 and scenario 4), while either improved fast charging speed (from 30 mins to 15 mins) or the provision of government subsidy (50,000 RMB for BEVs and 35,000 RMB for PHEVs following the actual Chinese government subsidy) would only reduce the market share of PVs by about 2%, which implies the more effective roles of providing home charging and free vehicle license than enhancing fast charging speed or providing government subsidy that are typically implemented in the market. If all four attributes are improved simultaneously, the market share of PVs can be reduced by over 14% and the market shares of PHEVs and BEVs can increase by about 10% and 4.2% respectively. It is worth noting that the purpose of this simulation is to compare the policy effectiveness of the key attributes, rather than forecasting the market share of EVs, as the latter also depends on the actual attributes observed by consumers in the real market conditions and, importantly, some factors such as vehicle price, fuel price and the availability of different alternatives may change over time (Qian and Soopramanien, 2015).

4. Discussion and Conclusions

4.1. Specific contributions and summary of key insights

Our first contribution concerns the role of service attributes in promoting EV adoption. The majority of previous work on the adoption of EVs has placed greater emphasis on the impact of product attributes than on service attributes. More recent research has started to acknowledge the role of service attributes, such as the availability of charging facilities and charging speed (Helveston et al., 2015; Hoen and Koetse, 2014; Jensen et al., 2016; Jensen et al., 2014; Qian and Soopramanien, 2011; Tanaka et al., 2014; Ziegler, 2012). In addition to including product attributes, this research differentiates between three types of provisions for EV charging services available in China: fast charging/battery swapping, public/workplace charging, and home charging. Importantly, compared to previous research that has also studied the importance of service attributes, we consider all the available types of charging/refuelling services in consideration of service availability and service speed. Therefore, this study contributes to the literature by identifying which service attribute(s) and which aspects of these attributes are most valued by consumers for the adoption of EVs. Our results show that, amongst all the service attributes considered in this study, home charging has the biggest and most significant effect on the adoption of EV. This demonstrates how important it is for potential car buyers to have exclusive access to a charging facility and, in particular, the convenience of having it at home. This should be compared to the inconvenience of having to find and use a public charging facility; the provision of such public service is not as valued by consumers. Therefore, although the previous studies have typically focused on the effects related to the public charging facilities (e.g. Hackbarth and Madlener, 2013, 2016; Tanaka et al., 2014), we highlight that consumers would value the home charging capability more, when they are offered to have such a service in the convenience of their home.

Our second contribution concerns the role of government policies. As with service attributes, we are able to evaluate which specific policy will be most effective. It is acknowledged that governments can play an active role in incentivising the purchase of EVs by offering incentives such as subsidies, tax exemptions, allowing use of bus/fast lanes (Lieven, 2015). This research investigates the effects of policies that have been implemented in some Chinese cities. These types of policies are unique to the Chinese car market, and as far as we are aware, their respective impacts on the adoption of EVs have not been sufficiently investigated. Some policies are designed to restrict the growth of private ownership of cars, particularly PVs. Other policies are designed to proactively encourage consumers to consider purchasing EVs, for example, subsidies that reduce the cost of purchasing EVs. The lottery process for the allocation of license plates for privately owned vehicles is designed to control the growth of private car ownership. However, the allocation of license plates is less restrictive if buyers choose to buy EVs rather than PVs. Our results indicate that if a buyer chooses to buy an EV, the specific policy of obtaining a free license immediately has a far greater effect than the monetary incentive of a 10,000 RMB government subsidy. Importantly, this effect must also be compared to the inconvenience of waiting for a license if one buys a PV. Importantly, compared to other government policy measures, this policy has the feature of neither using government funds, such as subsidy or tax exemption, nor interfering with other road users like the free use of bus lanes.

4.2. Policy implications

Promoting the adoption of EVs is a key policy initiative on the agenda of many governments' sustainable transportation policies. To meet these targets about sustainable transport systems, effective policy levers must be deployed. In our research context, it is important to identify the factors that are important when consumers are considering whether to buy EVs or PVs. For policy implications, our research demonstrates that generally car buyers have heterogeneous preferences towards the different types of vehicles and related attributes. Firstly, the superior performance of the ECL model specification, compared to the MNL model, generally indicates the presence of (unobserved) preference heterogeneity of Chinese consumers when they are considering adopting EVs. Secondly, we account for the systematic taste variations among consumers. Our empirical study finds that consumers in Tier-1 cities value the fast and slow service speeds more than those in non-Tier-1 cities. Therefore, our findings provide a more precise and effective policy framework which proposes that the governments or local authorities in Tier-1 cities should legislate or facilitate better service provisions, such as improved charging service speed to cater for local preference for faster speed, and supporting installation of EV charging facilities in residential compounds and implementing EV-friendly vehicle licensing policy to effectively incentivize EV adoption.

The literature on switching costs (Burnham et al., 2003) argues that we must consider carefully how consumers perceive the risks and benefits of the current ‘mainstream’ option and how they perceive the risks and benefits of the new option to which it is hoped consumers will switch. When we apply the switching cost framework to the adoption of EVs and how these costs can be reduced through the provisions of service attributes and government intervention, our results generally indicate that policies must be designed to acknowledge that consumers highly value ‘convenience’. This is supported in our results when we consider the level of importance that consumers attach to obtaining a vehicle license immediately and being able to easily access a charging facility and, preferably, one which provides fast charging. The important implication in relation to consumers’ propensity to switch to EVs is that policies that are designed to reduce the disutility of using EVs are less effective than policies that enhance the comparative value of using EVs. Our study thus raises an important general issue regarding the design of public policies that are intended to increase the adoption of EVs in other car markets: It is important to consider that consumers are thinking about the utility of using all types of cars and this implies that current policies that tend to mostly address the main points of using one particular type of car, i.e. EVs, may be less effective.

References

Armstrong, P., Garrido, R., Ortúzar, J. de D., 2001. Confidence intervals to bound the value of time. Transportation Research Part E: Logistics and Transportation Review 37(2), 143-161.

Atsmon, Y., Kertesz, A., Vittal, I., 2011, Is your emerging-market strategy local enough? Accessed September 13, 2011, from http://www.mckinsey.com/insights/growth/is_your_emerging-market_strategy_local_enough.

Burnham, T.A., Frels, J.K., Mahajan, V., 2003. Consumer switching costs: a typology, antecedents, and consequences. Journal of the Academy of marketing Science 31(2), 109-126.

Carley, S., Krause, R.M., Lane, B.W., Graham, J.D., 2013. Intent to purchase a plug-in electric vehicle: A survey of early impressions in large US cites. Transportation Research Part D: Transport and Environment 18, 39-45.

Caussade, S., Ortúzar, J. de D., Rizzi, L.I., Hensher, D.A., 2005. Assessing the influence of design dimensions on stated choice experiment estimates. Transportation Research Part B: Methodological 39(7), 621-640.

Chen, H., Ng, S., Rao, A.R., 2005. Cultural Differences in Consumer Impatience. Journal of Marketing Research 42(3), 291-301.

Chen, X., Zhao, J., 2013. Bidding to drive: Car license auction policy in Shanghai and its public acceptance. Transport Policy 27, 39-52.

China Association of Automobile Manufacturers, 2016, Economic Situations of Automobile Industry in 2015. Accessed from http://www.auto-stats.org.cn/ReadArticle.asp?NewsID=9179.

Dagsvik, J.K., Liu, G., 2009. A framework for analyzing rank-ordered data with application to automobile demand. Transportation Research Part A: Policy and Practice 43(1), 1-12.

Delucchi, M.A., Lipman, T.E., 2001. An analysis of the retail and lifecycle cost of battery-powered electric vehicles. Transportation Research Part D: Transport and Environment 6(6), 371-404.

Dimitropoulos, A., Rietveld, P., Van Ommeren, J.N., 2013. Consumer valuation of changes in driving range: A meta-analysis. Transportation Research Part A: Policy and Practice 55, 27-45.

Franke, T., Krems, J.F., 2013. Interacting with limited mobility resources: Psychological range levels in electric vehicle use. Transportation Research Part A: Policy and Practice 48, 109-122.

Gatta, V., Marcucci, E., Scaccia, L., 2015. On finite sample performance of confidence intervals methods for willingness to pay measures. Transportation Research Part A: Policy and Practice 82, 169-192.

GfK Group, 2014, International Trend and China Perspective of Automobile Consumption. Accessed July 8, 2018, from http://www.199it.com/archives/271976.html.

Greene, W.H., 2012. NLOGIT 5.0. Econometric Software Inc., New York.

Greene, W.H., Hensher, D.A., 2007. Heteroscedastic control for random coefficients and error components in mixed logit. Transportation Research Part E: Logistics and Transportation Review 43(5), 610-623.

Grisolía, J.M., López, F., Ortúzar, J. de D., 2015. Increasing the acceptability of a congestion charging scheme. Transport Policy 39, 37-47.

Hackbarth, A., Madlener, R., 2013. Consumer preferences for alternative fuel vehicles: A discrete choice analysis. Transportation Research Part D: Transport and Environment 25, 5-17.

Hackbarth, A., Madlener, R., 2016. Willingness-to-pay for alternative fuel vehicle characteristics: A stated choice study for Germany. Transportation Research Part A: Policy and Practice 85, 89-111.

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

Hauser, J.R., Tellis, G.J., Griffin, A., 2006. Research on innovation: A review and agenda for Marketing Science. Marketing Science 25(6), 687-717.

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

Hensher, D.A., Rose, J.M., Greene, W.H., 2005. Applied choice analysis: a primer. Cambridge University Press, Cambridge; New York.

Hensher, D.A., Rose, J.M., Greene, W.H., 2015. Applied choice analysis, Second ed. Cambridge University Press, Cambridge.

Hoen, A., Koetse, M.J., 2014. A choice experiment on alternative fuel vehicle preferences of private car owners in the Netherlands. Transportation Research Part A: Policy and Practice 61, 199-215.

Hofstede, G., 2001. Culture's Consequences: Comparing Values, Behaviors, Institutions, and Organizations across Nations, 2nd ed. Sage Publications, Thousand Oaks, CA.

Hofstede, G., Bond, M.H., 1988. The Confucius connection: From cultural roots to economic growth. Organizational Dynamics 16(4), 5-21.

Jensen, A.F., Cherchi, E., Mabit, S.L., 2013. On the stability of preferences and attitudes before and after experiencing an electric vehicle. Transportation Research Part D: Transport and Environment 25, 24-32.

Jensen, A.F., Cherchi, E., Mabit, S.L., Ortúzar, J. de D., 2016. Predicting the Potential Market for Electric Vehicles. Transportation Science 51(2), 427-440.

Jensen, A.F., Cherchi, E., Ortúzar, J. de D., 2014. A long panel survey to elicit variation in preferences and attitudes in the choice of electric vehicles. Transportation 41(5), 973-993.

Lamberton, C.P., Rose, R.L., 2012. When is ours better than mine? A framework for understanding and altering participation in commercial sharing systems. Journal of Marketing 76(4), 109-125.

Larson, P.D., Viáfara, J., Parsons, R.V., Elias, A., 2014. Consumer attitudes about electric cars: Pricing analysis and policy implications. Transportation Research Part A: Policy and Practice 69, 299-314.

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

Lieven, T., Mühlmeier, S., Henkel, S., Waller, J.F., 2011. Who will buy electric cars? An empirical study in Germany. Transportation Research Part D: Transport and Environment 16(3), 236-243.

Liu, J., 2012. Electric vehicle charging infrastructure assignment and power grid impacts assessment in Beijing. Energy Policy 51(0), 544-557.

McFadden, D., Train, K., 2000. Mixed MNL models for discrete response. Journal of Applied Econometrics 15(5), 447-470.

National Development and Reform Commission of China, 2012. The People's Republic of China National Report on Sustainable Development, accessed January 14, 2013, from http://www.sdpc.gov.cn/xwzx/xwtt/t20120601_483687.htm.

Ortúzar, J. de D., Willumsen, L.G., 2011. Modelling transport, 4th ed. Wiley, New Jersey.

Plötz, P., Schneider, U., Globisch, J., Dütschke, E., 2014. Who will buy electric vehicles? Identifying early adopters in Germany. Transportation Research Part A: Policy and Practice 67, 96-109.

Potoglou, D., Kanaroglou, P.S., 2007. Household demand and willingness to pay for clean vehicles. Transportation Research Part D: Transport and Environment 12(4), 264-274.

Potoglou, D., Kanaroglou, P.S., 2008. Disaggregate demand analyses for conventional and alternative fueled automobiles: A review. International Journal of Sustainable Transportation 2(4), 234-259.

Qian, L., Soopramanien, D., 2011. Heterogeneous consumer preferences for alternative fuel cars in China. Transportation Research Part D: Transport and Environment 16(8), 607-613.

Qian, L., Soopramanien, D., 2014. Using diffusion models to forecast market size in emerging markets with applications to the Chinese car market. Journal of Business Research 67(6), 1226-1232.

Qian, L., Soopramanien, D., 2015. Incorporating heterogeneity to forecast the demand of new products in emerging markets: Green cars in China. Technological Forecasting and Social Change 91, 33-46.

Qian, L., Yin, J., 2017. Linking Chinese cultural values and the adoption of electric vehicles: The mediating role of ethical evaluation. Transportation Research Part D: Transport and Environment 56, 175-188.

Rennings, K., 2000. Redefining innovation - eco-innovation research and the contribution from ecological economics. Ecological Economics 32(2), 319-332.

Rose, J.M., Bliemer, M.C.J., 2009. Constructing Efficient Stated Choice Experimental Designs. Transport Reviews: A Transnational Transdisciplinary Journal 29(5), 587-617.

Rose, J.M., Bliemer, M.C.J., Hensher, D.A., Collins, A.T., 2008. Designing efficient stated choice experiments in the presence of reference alternatives. Transportation Research Part B: Methodological 42(4), 395-406.

Schuitema, G., Anable, J., Skippon, S., Kinnear, N., 2013. The role of instrumental, hedonic and symbolic attributes in the intention to adopt electric vehicles. Transportation Research Part A: Policy and Practice 48, 39-49.

Sha, S., Huang, T., Gabardi, E., 2013, Upward Mobility: The Future of China's Premium Car Market. McKinsey & Company, Shanghai, Chinafrom.

Tanaka, M., Ida, T., Murakami, K., Friedman, L., 2014. Consumers' willingness to pay for alternative fuel vehicles: A comparative discrete choice analysis between the US and Japan. Transportation Research Part A: Policy and Practice 70, 194-209.

The State Council of China, 2014. Notice of the State Council on Adjusting the Standards for Categorizing City Sizes, Beijing, accessed November 29, 2014, from http://www.gov.cn/zhengce/content/2014-11/20/content_9225.htm.

The State Council of the People's Republic of China, 2012. Development Plans of Energy-Saving and New Energy Vehicle Industry (2012-2020), Beijing, from http://www.gov.cn/zwgk/2012-07/09/content_2179032.htm.

The World Bank, 2015. World Development Indicators.

Train, K.E., 2009. Discrete choice methods with simulation, 2nd ed. Cambridge University Press, New York.

Valeri, E., Danielis, R., 2015. Simulating the market penetration of cars with alternative fuelpowertrain technologies in Italy. Transport Policy 37, 44-56.

Wan, Z., Sperling, D., Wang, Y., 2015. China's electric car frustrations. Transportation Research Part D: Transport and Environment 34, 116-121.

Wang, A., Liao, W., Hein, A.-P., 2012, Bigger, Better, broader: A perspective on China's auto market in 2020. Accessed September 13, 2014, from http://mckinseychina.com/bigger-better-broader-a-perspective-on-chinas-auto-market-in-2020/.

Wang, N., Pan, H., Zheng, W., 2017. Assessment of the incentives on electric vehicle promotion in China. Transportation Research Part A: Policy and Practice 101, 177-189.

Wang, Q., 2015, June 30. Problems encountered after buying new energy cars: Did not expect the difficulties to install charging posts. Beijing Evening News, p. 19. Accessed February 3, 2016, from http://bjwb.bjd.com.cn/html/2015-06/30/content_291621.htm

Williams, A., 2007. Product service systems in the automobile industry: contribution to system innovation? Journal of Cleaner Production 15(11–12), 1093-1103.

Xing, M., Bao, J., Chen, H., 2016, Policy Details in 11 Cities: Guide to Buy EVs in 2016. Accessed June 20, from http://www.autohome.com.cn/news/201605/888319-all.html.

Yang, J., Liu, Y., Qin, P., Liu, A.A., 2014. A review of Beijing's vehicle registration lottery: Short-term effects on vehicle growth and fuel consumption. Energy Policy 75, 157-166.

Yang, X., Jin, W., Jiang, H., Xie, Q., Shen, W., Han, W., 2017. Car ownership policies in China: Preferences of residents and influence on the choice of electric cars. Transport Policy 58, 62-71.

Ziegler, A., 2012. Individual characteristics and stated preferences for alternative energy sources and propulsion technologies in vehicles: A discrete choice analysis for Germany. Transportation Research Part A: Policy and Practice 46(8), 1372-1385.

Table 1: Attributes and levels in stated choice experiment

Attributes	Variables	Alternatives: PVs	PHEVs	BEVs
Product Attributes				
Vehicle purchase price (10,000 RMB)	Price_{ni}	Specified by the respondents	(1). 20% higher than similar-sized PVs (2). 40% higher than similar-sized PVs (3). 60% higher than similar-sized PVs	(1). 30% higher than similar-sized PVs (2). 50% higher than similar-sized PVs (3). 70% higher than similar-sized PVs
Annual running cost (10,000 RMB)	$\mathrm{RunCost}_{ni}$	Market average level based on vehicle price level	(1). 40% of that of similar-sized PVs (2). 50% of that of similar-sized PVs (3). 60% of that of similar-sized PVs	(1). 10% of that of similar-sized PVs (2). 25% of that of similar-sized PVs (3). 40% of that of similar-sized PVs
Driving range (after full refuelling)	Range_{ni}	600 km (petrol)	(1). 50 km (electricity) + 600 km (petrol) (2). 70 km (electricity) + 600 km (petrol) (3). 100 km (electricity) + 600 km (petrol)	(1). 80 km (electricity) (2). 150 km (electricity) (3). 200 km (electricity)
Service Attributes				
Coverage of public fast service stations	$\mathrm{FastSERV}_{ni}$	100% (all existing petrol stations)	(1). 10% of existing petrol stations (2). 40% of existing petrol stations (3). 70% of existing petrol stations	Same as the levels for PHEVs
Service speed in public fast service stations	$\mathrm{FastSpeed}_{ni}$	5 mins (petrol refuelling)	(1). 10 mins (fast charging) (2). 20 mins (fast charging) (3). 30 mins (fast charging)	(1). 5 mins (battery swapping) (2). 15 mins (fast charging) (3). 30 mins (fast charging)
Coverage of workplace/public slow charging posts	$\mathrm{SlowPost}_{ni}$	NA	(1). 10% of available parking spaces (2). 40% of available parking spaces (3). 70% of available parking spaces	Same as the levels for PHEVs
Permission to install home slow charging post	$\mathrm{HomePost}_{ni}$	NA	(1). Yes (2). No	Same as the levels for PHEVs
Charging speed in slow charging post	$\mathrm{SlowSpeed}_{ni}$	NA	(1). 4 hours (2). 6 hours (3). 8 hours	(1). 6 hours (2). 8 hours (3). 10 hours
Public Policies				
Government subsidy (10,000 RMB)	$\mathrm{Subsidy}_{ni}$	No subsidy	(1). 0% of purchase price (2). 10% of purchase price (3). 20% of purchase price	(1). 10% of purchase price (2). 20% of purchase price (3). 30% of purchase price
Vehicle-licensing policy	$\mathrm{Licensing}_{ni}$	Lottery-based licensing	(1). Free license immediately (2). Lottery-based licensing	(1). Free license immediately (2). Lottery-based licensing

Table 2: Experiment design process

Stage	Step	Actions
I	1	First draft of a pre-pilot. Attributes based on previous works, experts' interviews and our own knowledge about the market.
	2	Initial list of attributes and levels for the pre-pilot test
	3	Experimental design for pre-pilot • Using Ngene • Orthogonal design • 32 scenarios
II	4	Pre-pilot survey for 60 individuals
III	5	Modelling results and analysis
	6	New list of attributes and levels
	7	New experimental design for pilot • Using VBA excel programme • D-efficient design • 24 scenarios-(6 scenarios per respondent)
IV	8	Pilot survey for 54 individuals
V	9	Pilot results, model and analysis
	10	New design of attributes and levels
VI	11	New and final experimental design • Using VBA Excel programme • D-efficient design • 24 scenarios-(6 scenarios per respondent)
	12	Final survey

Table 3: Summary of sample demographic characteristics (*N* = 1076)

Demographic Characteristics	Frequency	Percentage
Gender (male)	593	55.11%
Age		
18 to 30	492	45.72%
31–40	189	17.57%
41–50	341	31.69%
51 and older	54	5.02%
Education level		
High school and lower	183	17.01%
Junior college	152	14.13%
University	741	68.87%
Annual household income		
Less than 100K RMB	286	26.58%
Between 100K and 200K RMB	437	40.61%
Between 200K and 300K RMB	159	14.78%
Between 300K and 400K RMB	75	6.97%
More than 400K RMB	119	11.06%
Family size		
2 members and fewer	101	9.39%
3 members	587	54.55%
4 members	216	20.07%
5 members and more	172	15.99%
Tier of residential city ǂ		
Tier 1: more than 10 million	96	8.92%
Tier 2: between 5 million and 10 million	163	15.15%
Tier 3: between 3 million and 5 million	271	25.19%
Tier 4: between 1 million and 3 million	233	21.65%
Tier 5 and lower: fewer than 1 million	313	29.09%
Family fleet size		
0 car	191	17.75%
1 car	626	58.18%
2 cars	216	20.07%
3 cars and more	43	4.00%

ǂ The classification of city tiers in China follows the recent national standard from the State Council of China (http://www.gov.cn/zhengce/content/2014-11/20/content_9225.htm)

Table 4: Estimation results of the MXL model

Types of Attribute	Variables	coefficient		t-ratio
ASCs ǂ	BEVs	1.625		0.649
	PHEVs	3.721	**	2.896
Product attributes	Vehicle purchase price	-0.055	***	-3.478
	Annual running cost	-0.559	***	-4.230
	Driving range for BEVs	0.003	†	1.890
	Driving range for PVs and PHEVs	0.002		0.592
Service attributes	Coverage of public fast service stations	0.005		1.427
	Service speed in public fast service station	-0.013	*	-2.184
	Service speed in public fast service station * Tier 1 cities [d]	-0.017		-0.919
	Coverage of workplace/public slow charging posts	-0.001		-0.323
	Permission to install home slow charging post	0.504	***	3.400
	Charging speed in slow charging posts	-0.045		-1.448
	Charging speed in slow charging posts* Tier 1 cities [d]	-0.093		-1.407
Policy attributes	Government subsidy	0.061	**	2.886
	Free vehicle licensing	0.587	***	6.167
Socioeconomic factors interacted with ASCs	BEVs * Aged 18–30[a]	-1.999	*	-2.012
	BEVs * Aged 31–40[a]	-2.290	*	-2.155
	BEVs * Aged 41–50[a]	-2.603	*	-2.542
	BEVs * Male	-1.358	**	-2.986
	BEVs * Household annual income 100k–200k RMB[c]	-1.043	*	-1.997
	BEVs * Household annual income 200k–300k RMB[c]	-0.969		-1.250
	BEVs * Household annual income 300k–400k RMB[c]	-1.190		-1.139
	BEVs * Household annual income above 400k RMB[c]	-1.711	†	-1.645
	BEVs * Family size[e]	0.263	†	1.792
	PHEVs * Aged 18–30[a]	-1.562	†	-1.721
	PHEVs * Aged 31–40[a]	-1.762	†	-1.814
	PHEVs * Aged 41–50[a]	-2.049	*	-2.221
	PHEVs * Male	-1.021	**	-2.606
	PHEVs * Household annual income 100k–200k RMB[c]	-0.743	†	-1.685
	PHEVs * Household annual income 200k–300k RMB[c]	-0.706		-1.013
	PHEVs * Household annual income 300k–400k RMB[c]	-1.594	†	-1.815
	PHEVs * Household annual income above 400k RMB[c]	-1.618	†	-1.806
Intended price ranges interacted with ASCs	BEVs * Intended Price Range (below 100k RMB) [f]	1.923	*	1.965
	BEVs * Intended Price Range (100k–200k RMB) [f]	1.222		1.507
	BEVs * Intended Price Range (200k–300k RMB) [f]	0.643		0.780
	PHEVs * Intended Price Range (below 100k RMB) [f]	1.183		1.490
	PHEVs * Intended Price Range (100k–200k RMB) [f]	0.451		0.691
	PHEVs * Intended Price Range (200k–300k RMB) [f]	-0.141		-0.208
Standard deviation of error component	ICEVs	2.844	***	11.161
	PHEVs	1.113	**	3.018
	BEVs	2.187	***	8.554

Number of parameters	41
Number of observations	1076 × 6
Log likelihood for constants-only model	-2448.157
Log likelihood of MNL at convergence	-2335.620
Log likelihood of MXL at convergence	-1777.793
McFadden ρ^2 index	0.274
Log-likelihood ratio test (MXL vs. MNL, DF = 3)	1115.654

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$, all for two-sided test.

ǂ PVs is the reference alternative for ASCs; [a] the base category for age is 51 years and older; [b] the base category for education level is non-university education; [c] the base category for income is less than 100k RMB; [d] the base category for city tier is non-tier 1 cities; [e] the number of family size is aggregated into a metric variable; [f] the base category is the intended price range above 300k RMB.

Table 5: Willingness to pay on key attributes

Attribute	**Point Estimation of WTP**	**95% Confidence Interval of WTP**	**Unit**
Annual running cost	10	[5; 24]	RMB/(RMB/year)
Driving range for BEVs	587	[-19; 1,689]	RMB/km
Service speed in public fast service station	2,424	[265; 6,417]	RMB/minute
Permission to install home charging post	91,039	[35,518; 215,910]	RMB/unit
Free vehicle licensing	106,144	[60,658; 230,666]	RMB/unit

Table 6: Simulations on key service and policy attributes

Attribute	**Base Scenario**	**Scenario 1**	**Scenario 2**	**Scenario 3**	**Scenario 4**	**Scenario 5**
Fast service speed	30mins	30mins	30mins	15mins	30mins	15mins
Home charging	No	No	Yes	No	No	Yes
Free vehicle license	No	No	No	No	Yes	Yes
Government subsidy (in 10,000 RMB)	0	5 (BEV) & 3.5 (PHEV)	0	0	0	5 (BEV) & 3.5 (PHEV)
Market Share of PVs	37.19%	34.82%	32.19%	35.18%	31.40%	23.00%
Market Share of PHEVs	45.59%	46.65%	49.34%	47.10%	49.94%	55.51%
Market Share of BEVs	17.22%	18.53%	18.47%	17.72%	18.66%	21.49%

Figure 1: Example of stated choice scenario

	Attributes	Petrol Vehicle	PHEV	BEV
Product attributes	Purchase price	RMB 80,000	RMB 128,000	RMB 136,000
	Running cost	RMB 20,000 per year	RMB 10,000 per year	RMB 5,000 per year
	Driving range	600 km (petrol)	100 km (electricity) + 600 km (petrol)	80 km (electricity)
Service attributes	Coverage of public fast service stations	100% (all existing petrol stations)	equivalent to 70% of existing petrol stations	equivalent to 70% of existing petrol stations
	Service speed in public fast service station	5 mins (petrol refuelling)	20 mins (fast charging)	30 mins (fast charging)
	Coverage of workplace/ public slow charging posts	NA	70% of available parking spaces	70% of available parking spaces
	Permission to install home slow charging post	NA	Yes, permitted	Yes, permitted
	Charging speed in slow charging post	NA	8 hours (slow charging)	10 hours (slow charging)
Policy attributes	Government subsidy	No subsidy	RMB 12,800 (10% of purchase price)	RMB 27,200 (20% of purchase price)
	Vehicle-licensing policy	Lottery-based licensing	Free license immediately	Lottery-based licensing

Given three vehicles described above, which one would you be most like to purchase?

(A) Petrol Vehicle; (B) PHEV; (C) BEV