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Examining Shanghai consumer preferences for electric vehicles and their attributes

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Abstract

In this study, we conducted a stated choice survey in Shanghai to examine the attitudes of Shanghai residents towards electric vehicles and their attributes. Multinomial Logit and Random Parameter Logit models were used to analyze the response data for three samples—the full sample, a subsample of potential electric vehicle purchasers, and a subsample of unlikely electric vehicle purchasers. We found that the respondents in each of the three groups preferred electric vehicles with a longer driving range, a shorter charging time, a faster maximum speed, lower pollution emissions, lower fuel cost, and a lower price. However, a comparison of the two subsamples showed that potential electric vehicle purchasers were willing to pay more than their counterparts for enhancing vehicle attributes. We also investigated the determinants of likely electric vehicle purchase and found a number of demographic characteristics that were statistically significant.

Keywords: Electric vehicles; Preferences; Stated choice experiment; Willingness to pay; Random Parameter Logit model

JEL classification: Q42, Q51

1. Introduction

Electric-powered vehicles have emerged as the most prominent representatives of what are commonly referred to as new energy vehicles (NEVs). Their zero-level carbon emissions, low energy consumption and relatively simple and mature technology have elevated electric vehicles to a leadership role in setting the future course of the auto industry. In China, the development of NEV industries, especially the electric car industry, is in line with this trend. The Chinese government not only vigorously fosters and develops NEV companies, but also actively promotes the application of NEV technology. In recent years, the Chinese central and local governments have increased subsidies for new energy vehicles. The expected increase in sales, however, has thus far not materialized.

Research on consumer attitudes towards NEVs began earlier in developed countries than in developing countries such as China. Such studies have examined the effects of demographic characteristics, vehicle attributes, social factors, and policy issues on consumer preferences for NEVs. Power (2008) carried out a large-scale survey of 44,931 drivers in the US and found that highly educated and higher-income consumers were more willing to purchase an NEV. Furthermore, they found that, based on health issues, older drivers were more likely to consider an NEV. In contrast, Potoglou and Kanaroglou (2007) identified middle-income consumers as having the highest potential for purchasing an NEV. Gao and Kitirattragarn (2008) interviewed New York taxi owners and found that younger owners, those who had been in the job for a shorter time, and those who had higher incomes were more willing to consider buying a hybrid vehicle. Flamm (2009) surveyed consumers in Sacramento, California, using knowledge-attitude-behavior questionnaires and concluded that families exhibiting an environmental awareness were more likely to buy cars with high energy efficiency. Similarly, Peters et al. (2011) found that a consumer’s degree of concern regarding environmental issues and awareness of environmental behaviors influenced the decision to purchase an NEV, although the symbolic meaning associated with NEVs can have a negative effect on the willingness of an individual to pay for such a vehicle. In several other studies, the adoption of electric vehicles was shown to be motivated by environmental attitudes (Carley et al., 2013; Krupa et al., 2014). Kang and Park (2011) investigated factors influencing Korean consumers' acceptance of hydrogen fuel cell vehicles. Their results suggested that perceived risk, perceived benefits, consumer needs, consumer values, product perception, product experience, personal values (such as concern for the environment and a belief that individual efforts will bring positive results) affect acceptance. Erdem et al. (2010) demonstrated that factors such as gender, education level, wage, marital status, environmental awareness, risk attitude, acceptance of new technology, and the number of household-owned cars significantly affect the willingness of consumers to pay for hybrid electric vehicles (HEVs). Their research also pointed out that familiarity with the performance of cars was a significant factor affecting HEV purchases.

The earliest research on the influence of various NEV properties and performance features on consumer preferences dates back to the 1990s. Ewing and Sarigöllü (1998) used discrete choice experiments involving three alternatives (traditional cars, electric vehicles, and high fuel utilization vehicles) for US residents. They found that the price of the car, maintenance costs, speed performance, charging time, driving range, and pollution emission levels significantly affected the choice between an electric car and a higher fuel utilization vehicle. Caulfield et al. (2010) found that Irish consumers were more interested in attributes such as safety, reliability, and fuel costs than they were in the price of the car or its pollution emission level. In examining consumer attitudes towards natural gas vehicles, Saldarriaga-Isaza and Vergara (2009) surveyed Colombian residents and found that such factors as the size of the engine, whether the vehicle was owned by a company, price, and weekly mileage affected the decision to purchase a natural gas vehicle. They also showed that consumers who were familiar with incentive policies that promoted NEV ownership and use, as well as individuals with a higher education level, were more willing to accept natural gas vehicles. Zhang et al. (2011) targeted private car owners in Nanjing, China, and found that they chose NEVs mainly based on purchasing pressure (the influence of friends, legal or regulatory requirements, tax incentives for purchasing alternative fuel vehicles, etc.) and product attraction. Hidrue et al. (2011) specifically quantified how various levels of NEV performance affected an individual's willingness to pay for an electric vehicle. In a web-based survey of 3,029 US residents, they showed that, in addition to age and education, green consumption and expectations of gasoline prices were important influences. They also reported that specific properties of the car such as driving range, charging time to full power, pollution emissions, cost of energy consumption, and relative speed had a more critical impact on the consumer's willingness to pay than did the individual's demographic characteristics. Such results suggest that safety, reliability, acquisition cost, driving range, charging time, and charging mode are significant factors for potential NEV purchasers. Jensen et al. (2013) investigated whether a consumer's choice of an electric vehicle was influenced by driving range, top speed, battery life, and fuel cost. They found that driving range was the major concern. In contrast, Degirmenci and Breitner (2017) argued that the environmental performance of electric vehicles was a stronger predictor than price and range confidence, asserting that the environmental properties of electric vehicles are more important than their general attributes.

With respect to social influences, interpersonal network factors and social utilitarian factors appear to play a vital role in the decision to purchase an NEV. Heffner et al. (2007) pointed out that the symbolic significance of these vehicles was an important factor in the early California new energy car market. This is somewhat similar to Lane and Potter's findings (Lane and Potter, 2006) that British consumers were not particularly aware of the cost, performance, and environmental impact of clean cars, but rather it was the hot news related to clean cars that most affected their purchase decision. The impact of interpersonal networks on the NEV purchase decision has been analyzed by a number of scholars. For example, Axsen and Kurani (2010) studied the influence of interpersonal relationships on the cognition of hybrid electric vehicles (HEVs). They concluded that the interpersonal relationships of potential buyers played a significant role in their evaluation of HEV technology, and that the closer the relationship, the greater the impact. This suggests that knowing an HEV expert or someone who has related expertise and skills can have a positive effect on an individual's willingness to pay for an HEV.

To assess the influence of policy factors, Ozaki and Sevastyanova (2010) conducted a survey of 1,484 Toyota Prius owners in the UK to determine their motives for buying a hybrid vehicle. They found that fiscal policy and related preferential policy were the main motivations for their purchase. Gallagher and Muehlegger (2010) predicted that exemption from business or income taxes could effectively increase the sales of hybrid electric vehicles. In examining the sales of hybrid vehicles in the US from 2000 to 2006, they found that the effects of a business tax exemption were obvious and significant. Similarly, Chandra et al. (2010) and Bjerkan et al. (2016) provided supportive evidence that purchase tax exemption policy and tax rebate policy were significant incentives for NEV purchasers. On the other hand, Diamond (2008) studied US residents to determine how government incentive policies affect the purchase of NEVs and found that such policies did not stimulate consumer demand for hybrid cars; rather, it was the price of gasoline that was the most significant factor.

In the current paper, we use stated choice survey data collected in Shanghai, China, to examine the attitudes of Shanghai residents towards electric vehicles (EVs) and investigate how Shanghai consumers value various vehicle attributes. We believe that our study makes three contributions to the literature: First, previous studies on the purchase of NEVs in China have been mainly focused on government policies (e.g., Luo, 2014) and the demographic characteristics of consumers (e.g., Zhang et al., 2011). To the best of our knowledge, there is no published stated choice survey research investigating Chinese consumer preferences for specific NEV attributes. We fill this void. Second, in addition to presenting empirical results for our full sample, we also provide results for two subsamples—potential EV purchasers and non-EV purchasers (that is, individuals who declare themselves unlikely to buy an EV in the next 10 years). We believe that these subsample results offer a more focused insight into Chinese consumer preferences. Third, we examine the determinants of being a potential EV purchaser. Taken as a whole, our study has important policy implications for promoting the development of NEVs in China.

The remainder of the paper is organized as follows: The next section describes elements of the survey. Section 3 presents the econometric issues. Empirical results are presented and discussed in Section 4. The final section offers conclusions and suggestions for further research.

2. Survey issues

2.1 Questionnaire

The questionnaire used in this study has three main parts: In the first part, respondents were presented with eight statements. A five-point Likert scale (strongly disagree, disagree, neither agree nor disagree, agree, and strongly agree) was used. The details of the statements are given in Table 1. As shown, the statements are not only related to environmental consciousness and green consumption, but also refer to specific characteristics of China as well as general NEV features. As an example, Statement 3 relates directly to China's current reality. For developing countries like China, there is an inevitable contradiction between economic development and environmental protection. How Chinese consumers view this conflict is extremely important to the country's future development.

Table 1. The statements revealing respondents' environmental consciousness

Statement 1	Environmental problems never bother me because I think environmental pollution problems are overestimated.
Statement 2	I have little or no fear that environmental problems will have an impact on myself and my family's health.
Statement 3	I can accept some of the developing countries like China have several pollution problems.
Statement 4	I am willing to pay more to buy environmentally friendly products.
Statement 5	I am willing to pay more to buy products with new technology.
Statement 6	I think that our consumption should be responsible for the environment.
Statement 7	Driving new energy vehicles can reduce the current environmental pollution.
Statement 8	I think that decreasing pollutant emission is important for me to choose a new energy vehicle.

The second section of the questionnaire targeted respondent preferences for various NEV attributes. In our experiment, a number of attributes and assigned levels were used to generate hypothetical choice sets. In each choice set, we presented three alternatives: Traditional Vehicle, Electric Vehicle 1, and Electric Vehicle 2. The Traditional Vehicle serves as the status quo alternative. As presented in Table 2, each electric vehicle has six attributes (driving range, pollution level, charging time, speed, fuel cost, and price) and each attribute has four levels. These attributes and their levels were determined through a careful pre-investigation of current electric vehicle market data. We used SAS to create the choice sets. A fractional factorial design was employed and 64 valid choice sets were generated. These choice sets were further randomly divided into 16 versions, with each version consisting of four choice sets. Table 3 presents an example of the choice sets. Based on traditional gasoline vehicle market data, fuel cost for the Traditional Vehicle was assumed to be 0.5 RMB/km; the price was from 120,000 to 150,000 RMB. It should be noted that these two values did not vary across the choice sets. They were presented solely to allow respondents to easily compare with the values for the other two alternatives.

Table 2. Attributes and their levels of electric vehicles

Attributes	Levels of attributes
Driving range (kilometers on a full charge)	100 km, 200 km, 300 km, 400 km
Pollution (compared to traditional vehicle)	Reduced by 25%, by 50%, by 75%, by 95%
Charging time (for traveling 100 km)	5 hours, 3 hours, 1 hour, 10 minutes
Maximum speed (compared to traditional vehicle)	10% slower, 5% slower, 5% faster, 10% faster
Fuel costs (RMB per kilometer)	0.35 RMB/km, 0.25 RMB/km, 0.2 RMB/km, 0.1 RMB/km
Price (compared to traditional vehicle)	6,000 RMB higher, 24,000 RMB higher, 50,000 RMB higher, 100,000 RMB higher

Table 3. An example of choice sets

Features	Traditional Vehicle	Electric Vehicle 1	Electric Vehicle 2
Driving range (full charge)	–	200 km	400 km
Pollution (compared to traditional vehicle)	–	75% reduced	95% reduced
Charging time (for traveling 100 km)	–	1 hour	3 hours
Maximum speed (compared to traditional vehicle)	–	5% faster	5% faster
Fuel cost	0.5 RMB/km	0.1 RMB/km	0.1 RMB/km
Price (compared to traditional vehicle)	120,000 to 150,000 RMB	100,000 RMB higher	100,000 RMB higher
Please choose one most-desirable vehicle by placing a √ in a ☐	☐	☐	☐

Questions in the third section of the questionnaire were related to demographic characteristics, which included gender, age, educational attainment, occupation, and annual income. Respondents were also asked whether they expected to own an electric vehicle sometime in the next 10 years. This yes/no question served as an indicator of potential EV purchase in our empirical analysis.

2.2 Data collection

Face-to-face interviews were conducted in Shanghai from December 2014 to November 2015. As venues for the survey, we chose 23 driving schools in the Baoshan, Hongkou, Jiading, Pudong, and Minhang districts, as well as a number of 4s automotive shops located in these same districts. We considered the likelihood of finding potential car buyers at these venues to be relatively high. Survey respondents were individuals who were seeking to obtain a driving license or who intended to buy a car.

A summary of the demographic characteristics of our survey respondents is provided in Table 4. Of the 760 respondents providing valid responses, 487 (64.1%) were male and 273 were female (35.9%). The proportion of male respondents in our sample was higher than that reported in the Shanghai Statistical Yearbook 2016, which shows the official 2015 male-female ratio as 49.6% versus 50.4%. The mean age of respondents was 34; only 0.8% were younger than 17 or older than 60. Approximately 63% of the respondents had an annual income of at least 100,000 RMB (about 14,500 USD, where 1 USD = 6.70 RMB), which was considerably higher than the overall average in Shanghai. This is mainly due to the venues that we chose for the survey, as respondents there were highly likely to be potential car purchasers with an income that would allow them to buy and maintain a car. As for education level, 19.5% of the respondents held at least a master’s degree, which was a higher percentage than the overall Shanghai percentage. Finally, more than half of the respondents showed an inclination to own an EV car in the next 10 years, and approximately 43% indicated that they pay attention to policies related to owning and driving an NEV.

Table 4. Demographic characteristics of the respondents (n = 760)

Demographic characteristics	% in sample
Gender	
Male	64.1%
Female	35.9%
Age (mean = 34)	
17 and below	0.4%
18-34	55.2%
35-59	43.9%
60 and above	0.4%
Educational attainment	
Bachelor degree or below	80.5%
Master degree or above	19.5%
Occupation	
Mid-level or manager in enterprise	14.4%
Salariat	27.0%
Entrepreneur	5.6%
Civil servant	11.0%
Professionals (teachers, doctors, lawyers, etc.)	14.4%
Others (student, freelance, etc.)	27.5%
Individual annual income (RMB)	
Less than 100,000	36.8%
100,000 - 200,000	39.5%
200,000 - 300,000	13.5%
300,000 - 400,000	5.2%
400,000 and above	5.0%
Family with cars	
Yes	62.7%
No	37.3%
Own an EV in the coming ten years	
Yes	54.5%
No	42.6%
No answer	2.9%
Pay attention to policies related to NEV	
No	17.9%
Neutral	38.7%
Yes	43.4%

3. Empirical methodology

3.1 Multinomial Logit model

The choice model in this study is based on random utility theory. The basic assumption in the random utility approach to choice modeling is that decision makers are utility maximizers; that is, given a set of alternatives, the decision maker will choose the alternative that maximizes his/her utility (Shen, 2006). Since the utility U of an alternative for an individual cannot be observed, it is assumed to consist of a deterministic component V and a random error term ε. Formally, the utility of alternative i for individual q can be expressed as:

$$U_{iq} = V_{iq} + \varepsilon_{iq} \tag{1}$$

Hence the probability that individual q chooses alternative i from a particular set J, which is composed of j alternatives, can be written as:

$$P_{iq} = P(U_{iq} > U_{jq}; \forall \quad i \neq j \in J) = P(\varepsilon_{jq} < \varepsilon_{iq} + V_{iq} - V_{jq}; \forall \quad i \neq j \in J) \tag{2}$$

To transform the random utility model into a choice model, certain assumptions about the joint distribution of the vector of random error terms are required. If the random error terms are assumed to follow the extreme value type I distribution and are assumed to be independently and identically distributed (IID) across alternatives and cases (or observations), the multinomial (or conditional) logit (MNL) model (McFadden, 1974) is obtained. In the MNL model, the choice probability in Equation (2) is expressed as:

$$P_{iq} = \exp(\mu V_{iq}) / \sum_{j=1}^{J} \exp(\mu V_{jq}) \tag{3}$$

If we make the further assumption that the deterministic component of utility is linear in its parameters, i.e., $V_{iq} = \beta' X_{iq}$, then Equation (3) can be given as:

$$P_{iq} = \exp(\mu \beta' X_{iq}) / \sum_{j=1}^{J} \exp(\mu \beta' X_{jq}) \tag{4}$$

where μ represents a scale parameter that determines the scale of the utilities, which is proportional to the inverse of the distribution of the error terms. Typically, it is normalized to 1 in the MNL model. X_{iq} are the explanatory variables of V_{iq}, normally including alternative-specific constants (ASCs), the attributes of alternative i, and the social-economic characteristics of individual q. β' is the parameter vector associated with vector X_{iq}.

It is well known that heterogeneity among individuals is extremely difficult to examine in the MNL model (Louviere et al., 2000; Shen, 2006). This limitation can be relaxed, to some extent, by interaction terms between individual-specific characteristics and the various choices. However, there is a limit to this method since it requires a priori selection of key individual characteristics and attributes and involves a limited selection of individual-specific variables (Boxall and Adamowicz, 2002).

3.2 Random Parameters Logit model

One approach that can account for individual heterogeneity is the Random Parameter Logit (RPL) (or Mixed Logit) model, which allows model parameters to vary randomly through assumed distributions (normal, log-normal, triangular, etc,). The model is a generalization of the MNL model and is summarized below:

$$P_{iqt} = \exp(\alpha' + \beta' X_{iqt} + \varphi' F_{iqt}) / \sum_{j=1}^{J} \exp(\alpha' + \beta' X_{jqt} + \varphi' F_{jqt}) \quad (5)$$

where

α' is a vector of fixed or random alternative-specific constants associated with $i = 1,...,J$ alternatives and $q = 1,...,Q$ individuals, where one of these ASCs should be identified as 0.

β' is a parameter vector that is randomly distributed across individuals.

φ' is a vector of non-random parameters.

X_{iqt} is a vector of individual-specific characteristics and alternative-specific attributes at observation *t*, and is estimated with random parameters.

F_{iqt} is a vector of individual-specific characteristics and alternative-specific attributes at observation *t*, and is estimated with fixed parameters.

In this specification, a subset or all of α' and the parameters in the β' vector can be assumed to be randomly distributed across individuals. These random parameters can also be defined as a function of the characteristics of individuals and/or other attributes that are choice invariant. Based on these defined attributes, the mean and standard deviations of the specified random parameters and contributions from these choice invariant attributes on random parameters are estimated by using the Maximum Simulated Likelihood (MSL) method. The RPL model is sufficiently flexible to provide the modeler a tremendous range within which to specify individual unobserved heterogeneity. To some extent, this flexibility offsets the specificity of the distributional assumptions (Greene and Hensher 2003).

4. Results

4.1 Preliminary comparison between potential EV and non-EV purchasers

Based on their answers to the question regarding expected EV ownership in the next 10 years, we divided the respondents into two categories—potential EV purchasers and non-EV purchasers. In this subsection, we present a simple comparison of the demographic characteristics (educational attainment, occupation, and income) of the respondents in these two categories. Formal Logit regression results are given in Subsection 4.3.

As shown in Figure 1, the proportion of potential EV purchasers holding at least a master's degree is significantly higher than that of non-EV purchasers (24.4% versus 14.5 %, $z = 11.54$, $p < 0.001$). This suggests that higher educational attainment may be an important factor affecting an individual's interest in owning an EV.

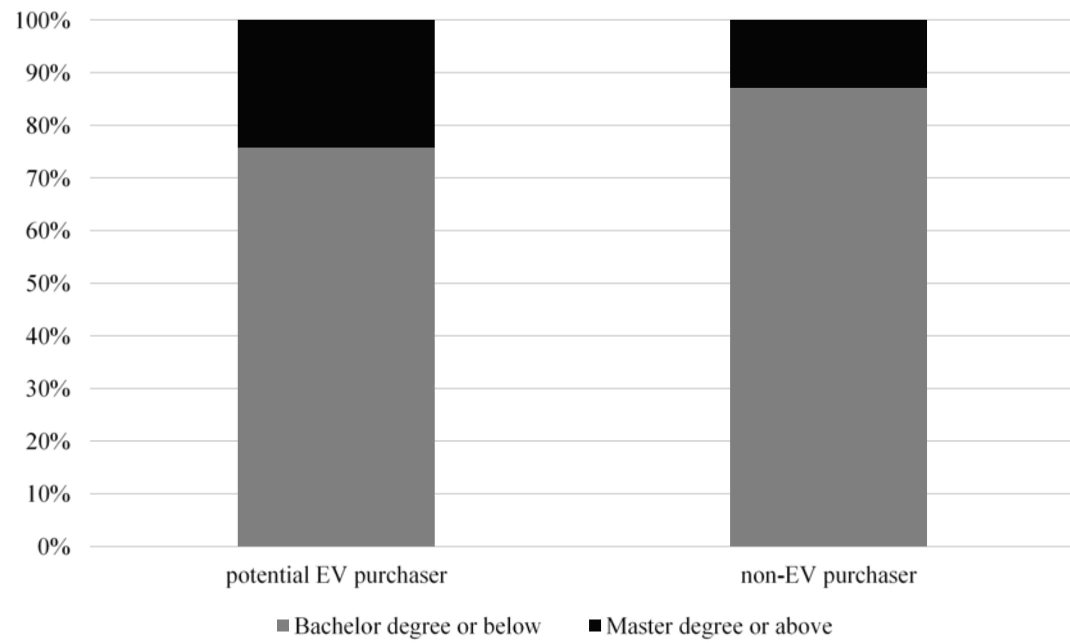

Figure 1. Educational attainment of potential EV and non-EV purchasers

Figure 2 shows the occupation distributions of potential EV and non-EV purchasers. While the distributions of the two groups are generally similar, more professionals and civil servants appear to prefer EVs. In addition, as can be seen in the distributions of annual income in Figure 3, respondents with higher incomes appear to be more willing to purchase an EV. This result is, to some extent, consistent with the results of the surveys of US consumers that are reported in Power (2008) and Gao and Kitirattragarn (2008).

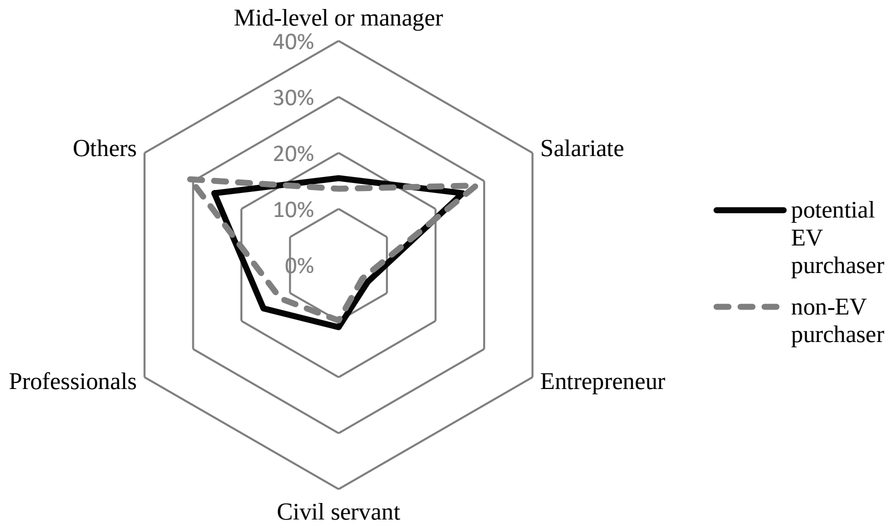

Figure 2. Occupation distribution of potential EV and non-EV purchasers

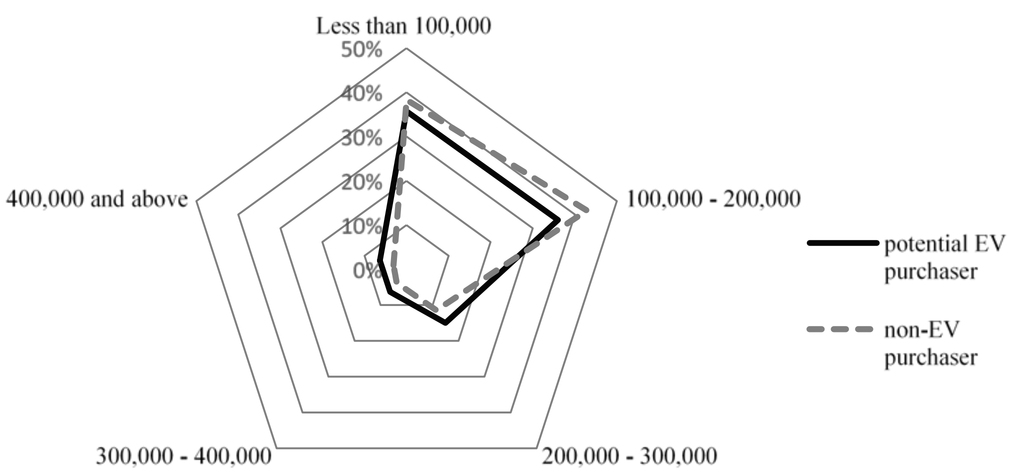

Figure 3. Income distribution of potential EV and non-EV purchasers

4.2 Results of the MNL and RPL regressions

Tables 5 and 6 give the results of the MNL and RPL models, respectively. In both models, estimates are shown for each of the three sample groups—the full sample, the subsample of potential EV purchasers, and the subsample of non-EV purchasers. The log likelihood values in the MNL model in all three cases were slightly lower than those in the RPL model, which suggests that the RPL model is statistically superior. In addition, a number of the standard deviations of the assumed random parameters in the RPL model are significant, which provides supportive evidence that taking unobserved individual heterogeneity into account is necessary. In both the MNL and RPL regressions, two of the EV attributes (driving range and charging time) were treated as discrete variables, while the other four attributes (pollution degree, maximum speed, fuel cost, and relative price) were treated as continuous variables.

4.2.1 Results of the full sample

Results of the MNL model for the full sample appear in the second column of Table 5. As shown, all the estimated parameters except in the case of *3 hours charging time* are statistically significant and have the expected signs. For example, relative to the base level of 100 km d*riving range*, the parameters of the three alternative levels (200 km, 300 km, and 400 km) are significant and positive, and their magnitudes increase with driving range. This implies that the respondents prefer an EV with a longer driving range. *Pollution degree* and *maximum speed* are significant, with the expected positive signs, suggesting that the respondents prefer an EV that offers greater pollution reduction and/or a higher maximum speed. Estimates of the parameters of the two cost variables (fuel cost and relative vehicle price) show negative signs, which is consistent with fundamental economic theory. The statistically insignificant parameter of *3 hours* c*harging time* suggests that the respondents may consider three hours to be essentially the same as five hours for EV charging.

In the RPL model, we assumed that the parameters of *driving range*, *charging time*, *pollution degree*, *maximum speed*, and *fuel cost* follow a normal distribution. In order to calculate easily our "willingness to pay" (WTP) values, we treated the parameter of *relative price* as fixed. As shown in the second column of Table 6, there appears to be little difference between the means of the parameters shown here and the MNL estimates with respect to both signs and significance. However, the estimated standard deviations of *pollution degree*, *fuel cost*, and *10 minutes charging time* shown in the third column are significant, indicating that there exists heterogeneity among respondents in their preferences for these attributes.

Table 5. Estimation results of the MNL model

	Full Sample	potential EV purchaser	Non-EV purchaser
EV1 Constant	0.316**	-0.318	0.832***
	(2.25)	(-0.71)	(3.74)
EV2 Constant	0.141***	0.209	0.503
	(3.19)	(3.62)	(0.74)
Driving range (100 km as the base)			
200 km	0.370 ***	0.485***	0.263***
	(4.60)	(4.55)	(2.01)
300 km	0.633 ***	0.606***	0.605***
	(7.87)	(5.56)	(4.69)
400 km	0.848***	0.822***	0.865***
	(10.38)	(7.53)	(6.56)
Charging time (5 hours as the base)			
3 hours	0.197	0.472	0.066
	(0.24)	(0.22)	(0.50)
1 hour	0.283***	0.319***	0.319**
	(3.52)	(3.02)	(2.42)
10 minutes	0.547***	0.595***	0.560***
	(6.96)	(5.69)	(4.33)
Pollution degree	0.747***	0.745***	0.899***
	(6.95)	(5.14)	(5.26)
Maximum speed	2.611*	3.138***	1.421**
	(7.19)	(6.24)	(2.51)
Fuel costs	-0.982***	-0.700*	-1.450***
	(-3.25)	(-1.72)	(-3.00)
Relative price	-0.126***	-0.100***	-0.173***
	(-14.74)	(-8.97)	(-12.00)
Log likelihood	-2955.81	-1499.50	-1282.76
Sample size	3040	1656	1296

Notes: ***, **, and * indicate statistically significant at 1%, 5%, and 10% level of confidence, respectively. Z-statistics are reported in parentheses.

Table 6. Estimation results of the RPL model

	Full sample		Potential EV purchaser		Non-EV purchaser	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
EV1 Constant	0.172		-0.904		0.807***	
	(0.77)		(-1.43)		(3.06)	
EV2 Constant	0.174***		0.329***		0.051	
	(2.85)		(2.60)		(0.62)	
Driving range (100 km as the base)						
200 km	0.505 ***	0.688	0.863***	1.551*	0.304**	0.302
	(4.08)	(1.21)	(3.20)	(1.90)	(1.97)	(0.56)
300 km	0.864 ***	0.393	1.161***	0.856	0.690***	0.123
	(5.51)	(0.79)	(3.65)	(0.92)	(4.28)	(0.28)
400 km	1.123***	0.167	1.405***	0.719	0.992***	0.053
	(6.41)	(0.54)	(3.34)	(1.09)	(5.71)	(0.08)
Charging time (5 hours as the base)						
3 hours	0.073	0.461	0.186	0.437	0.023	0.666
	(0.66)	(1.17)	(0.98)	(0.68)	(0.13)	(0.96)
1 hour	0.361***	0.773	0.584**	1.220*	0.336**	0.093
	(3.18)	(1.24)	(2.56)	(1.67)	(2.23)	(0.07)
10 minutes	0.697***	1.303***	1.224***	3.096***	0.592***	0.715
	(5.18)	(2.72)	(3.22)	(2.76)	(3.95)	(1.35)
Pollution degree	0.930***	1.486***	1.316***	2.755**	0.928***	1.291***
	(5.30)	(3.32)	(3.34)	(2.35)	(4.55)	(2.63)
Maximum speed	3.241***	2.323	5.604***	2.060	1.517**	2.671
	(5.23)	(0.61)	(3.34)	(0.56)	(2.32)	(0.70)
Fuel costs	-1.230***	4.145***	-1.615*	8.502**	-1.730***	0.788
	(-2.73)	(2.70)	(-1.75)	(2.56)	(-2.90)	(0.50)
Relative price	-0.157***		-0.174***		-0.193***	
	(-7.47)		(-3.96)		(-9.33)	
Log likelihood	-2945.83		-1483.76		-1279.15	
Sample size	3040		1656		1296	

Notes: ***, **, and * indicate statistically significant at 1%, 5%, and 10% level of confidence, respectively. Z-statistics are reported in parentheses.

4.2.2 Results of the subsamples

Based on a simple comparison of the subsample results presented in Tables 5 and 6, there appears to be very little difference in attribute preferences between potential EV purchasers and non-EV purchasers in both the MNL and RPL models. The only apparent difference is that several standard deviations of the random parameters in the RPL model are significant in the potential EV purchaser subsample but not in the non-EV purchaser subsample. This would seem to imply that there is heterogeneity among potential EV purchasers with respect to these attributes.

We also sought to determine whether there are differences in the willingness to pay values between the two subsamples. These values were calculated by dividing the parameters of the various attributes by the parameter of *relative price*.

Table 7 provides the WTP values for *driving range*, *charging time*, *pollution degree*, and *maximum speed* using both the MNL and RPL estimates. From the table, we find that (i) except for *3 hours* c*harging time*, all the WTPs are significant; (ii) all the WTP values in the subsample of potential EV purchasers are substantially higher than those in the subsample of non-EV purchasers, regardless of which model is used; (iii) the largest WTP disparity between potential EV purchasers and non-EV purchasers is for *maximum speed*, implying that improving the performance of this attribute might be the most important issue for attracting potential EV purchasers; and (iv) in the RPL model, the net increase in WTP for each 100 km increase in *driving range* diminishes among potential EV purchasers—from 49,598 RMB for a driving range increase from 100 km to 200 km, to 17,126 RMB for a driving range increase from 200 km to 300 km, and to 14,023 RMB for a driving range increase from 300 km to 400 km—implying that an overlong driving range might not be a must for potential EV purchasers.

Table 7. Willingness to pay values in the MNL and RPL models

	MNL model		RPL model	
	Potential EV purchaser	Non-EV purchaser	Potential EV purchaser	Non-EV purchaser
Driving range (100 km as the base)				
200 km	48,563***	15,202***	49,598***	15,751**
300 km	60,679***	34,971***	66,724***	35,751***
400 km	82,307***	50,000***	80,747***	51,399***
Charging time (5 hours as the base)				
3 hours	47,261	3,815	10,690	1,192
1 hour	31,942***	18,439**	33,563**	17,409**
10 minutes	59,577***	32,370***	70,345***	30,674***
Pollution degree	74,597***	51,965***	75,632***	48,083***
Maximum speed	314,208***	82,139**	322,069***	78,601**

Notes: ***, **, and * indicate statistically significant at 1%, 5%, and 10% level of confidence, respectively. The unit of the WTP values is RMB.

4.3 Determinants of being a potential EV purchaser

According to the WTP results reported above, potential EV purchasers are willing to pay more than non-EV purchasers for the enhancement of each of the EV attributes presented to them. In this sense, to promote EVs in China, it is extremely important to know what makes a person a potential EV purchaser.

Table 8. Factor analysis results

Variable	Factor1	Factor2	Factor3	Uniqueness
Statement 1	-0.1714	-0.0734	***0.6147***	0.5874
Statement 2	-0.0758	-0.0906	***0.6062***	0.6186
Statement 3	-0.0299	0.0190	***0.3505***	0.8759
Statement 4	0.2334	***0.6085***	-0.1277	0.5590
Statement 5	0.1452	***0.6111***	0.0025	0.6054
Statement 6	***0.4377***	0.3757	-0.1767	0.6360
Statement 7	***0.5891***	0.1284	-0.0779	0.6304
Statement 8	***0.6024***	0.2509	-0.1402	0.5545

Notes: Factors 1, 2, and 3 refer to green consumption consciousness, acceptance of new product and new technology, and environmental protection awareness.

We used a Logit regression model to examine the determinants of being a potential EV purchaser. In addition to treating demographic variables as independent variables in the model, we added variables related to the individual's environmental awareness and green consumption consciousness. These additional variables were identified by conducting a factor analysis of the eight items included in the first part of the questionnaire. In all, three new variables were created and added to the Logit regression. Our three-factor solution was supported by the KMO test (the overall KMO measure of sampling adequacy = 0.708). Table 8 presents the results of the factor analysis. As shown in the table, the first new variable (factor 1) is marked by high loadings on statements 6, 7, and 8, and refers to the respondent's green consumption consciousness; the second new variable (factor 2) is marked by high loadings on statements 4 and 5, and refers to the respondent's acceptance of new products and new technology; the third new variable (factor 3) is marked by high loadings on statements 1, 2, and 3, and refers to the respondent's environmental protection awareness. It should be noted that the larger the values of factor 1 and factor 2, the higher are the respondent's green consumption consciousness and the respondents' acceptance of new products and new technology, respectively. In contrast, the larger the value of factor 3, the lower is the respondent's environmental awareness.

Table 9 reports the Logit regression results. As indicated, males, highly educated residents with a degree at the master's level or higher, members of the salariat, and residents who pay attention to policies related to NEVs are more likely to be potential EV purchasers. On the other hand, managers or holders of mid-level positions and respondents in families that already own a car are less likely to be potential EV purchasers. Additionally, the probability of being a potential EV purchaser increases with age, individual annual income, green consumption consciousness, and acceptance of new products and new technology, but decreases with a decrease in environmental protection awareness. These Logit results are obviously important for both policy makers and EV manufactures, as understanding the factors that determine whether an individual is a potential EV purchaser can help both government and industry identify target consumers when devising new promotion policies or plans.

Table 9. Potential EV purchaser results from the Logit regression

Variable	Coefficient	Marginal effect
Constant term	-0.046	
Male	0.202***	0.050***
Age	-0.004	-0.001
Master degree or above	0.479***	0.117***
Individual annual income	0.092***	0.023***
Mid-level or manager	-0.351***	-0.086***
Salariat	0.126*	0.031*
Entrepreneur	-0.050	-0.012
Civil servant	-0.079	-0.019
Professionals (teachers, doctors, lawyers, etc.)	-0.056	-0.014
Family with cars	-0.149***	-0.037***
Pay attention to policies related to NEVs	0.712***	0.175***
Green consumption consciousness	0.258***	0.063***
Acceptance of new product and new technology	0.261***	0.064***
Environmental protection awareness	-0.102***	-0.025***
Log likelihood	-5072.30	
Sample size	680	

Notes: ***, **, and * indicate statistically significant at 1%, 5%, and 10% level of confidence, respectively. Z-statistics and/or standard errors are not reported for the sake of space saving.

5. Conclusion

We conducted a stated choice survey in Shanghai to investigate the electric vehicle preferences of Shanghai residents. MNL and RPL models were used to analyze data for three samples—the full sample, a subsample of potential EV purchasers, and a subsample of non-EV purchasers. We found that the respondents in all three samples preferred EVs with a longer driving range, a shorter charging time, a faster maximum speed, lower pollution emissions, lower fuel cost, and a lower price. A comparison of the two subsamples showed that potential EV purchasers were willing to pay more than their non-purchaser counterparts for enhancing each of the EV attributes presented to them. The determinants of being a potential EV purchaser were also investigated. We found that such factors as gender, age, educational attainment, occupation, income, green consumption consciousness, acceptance of new products and new technology, environmental protection awareness, whether the family already owns a car, and awareness of policies related to NEVs were significant factors.

With respect to policies to promote EVs, both the Chinese Central Government and the Shanghai Municipal Government have provided subsidies for purchasing EVs since 2013. Thus far, however, the subsidies have been focused on just one EV attribute—driving range. Since our empirical results offer supportive evidence that individuals are willing to pay for enhancing other EV attributes (e.g., reducing charging time, lowering pollution emissions, and increasing maximum speed), government consideration of subsidizing these other attributes would seem appropriate.

Since 2016, the Shanghai government has provided free license plates to EV owners. A private car license plate auction was introduced in Shanghai more than twenty years ago as a way to control the number of private vehicles. However, since the auction's introduction, the average winning price has continued to increase, while the chances of actually winning a plate have continued to decline. In May 2017, the average winning price soared to 90,209 RMB (about 13,464 USD, where 1 USD = 6.70 RMB), while the success rate fell to 3.8%. Given this circumstance, offering free license plates for EVs should be a very attractive "subsidy" to consumers and may be an important factor in their choosing an EV. We leave this issue open and welcome any efforts to explore it in greater depth.

Finally, it should be noted that our results are based on a hypothetical choice survey, which means that there may be a hypothetical bias. Future research is highly encouraged in order to facilitate a comparison of our results with results estimated from actual purchase data.

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