MPRA
Munich Personal RePEc Archive

How psychological factors related to consumer preferences on plug-in electric passenger vehicles in Chinese cities?A comparison of cities with and without restrictions

Yang, Jue and Chen, Fei

Zhejiang Sci-Tec University

20 May 2020

Online at https://mpra.ub.uni-muenchen.de/96165/
MPRA Paper No. 96165, posted 26 May 2020 14:57 UTC

Title:

How psychological factors related to consumer preferences on plug-in electric passenger vehicles in Chinese cities?A comparison of cities with and without restrictions

Jue Yang
Zhejiang Sci-Tec University
928 Second Revenue, Xiasha Higher Education Zone
Hangzhou, Zhejiang Province, P.R.China 310018
+86-180-5717-9397

Fei Chen
Zhejiang Sci-Tec University
928 Second Revenue, Xiasha Higher Education Zone
Hangzhou, Zhejiang Province, P.R.China 310018

Abstract

This study examines the impacts of psychological factors on Chinese consumers' preferences of PEV features as well as PEV uptake intension in cities with and without license number plate restrictions. Psychological factors are relatively less investigated factors in the domestic literature, but consumers may not behave rational as researchers expected when facing such a complex choice problem. This study generates three latent psychological factors, namely knowledge of policy and PEVs, social influence, and environmental attitudes/innovativeness, and integrates them with object-case best-worst scaling model through a hybrid choice model. Evidences show that knowledge and environmental attitudes are weaker compare to social influence and innovativeness, but these factors affect consumers' preferences differently both at individual level and city level. To facilitate market-oriented PEV uptake, especially in areas without restrictions, improve reputation through interpersonal communication on technical features are expected. While in large cities with restrictions, through neighborhood effects and innovativeness, emphasizing air pollution and CO_2 emission reduction features could be more efficient.

1. Introduction

As an important pathway for mitigating climate change, increasing the share of plug-in electric vehicles (PEVs)[1] in auto market is a big challenge in many countries including China (Sykes and Axsen 2017). Although exponential growth has been achieved across the world since 2010, total accumulate sales of PEVs only stood for approximately 2.2% of all auto sales in 2018 (EV data center, 2019). China, as the largest market, delivered 1.2 million units of new energy vehicle (NEV)[2] in year 2018 and 2019 (China Association of Automobile Manufacturers, 2020). High subsidies for NEVs and restriction policy to internal combustion engine vehicles (ICEV), are considered as the most powerful drivers to promote the NEV adoptions (Ou et al. 2019), which achieved approximately 4.7% of auto sales in 2019 (CAAM, 2020). The latest released version of the consultation draft of Development Plan for New Energy Automobile Industry 2021-2035 (MIIT, 2019) proposes a target of 25% market penetration of NEVs by 2025. This target requires at least 3.33% annual growth rate of NEVs during the next six years. However, with the slowdown of Chinese economic growth and steep cut in subsidies (almost 50% cut) From June.25th 2019, sales of NEV in China showed a much lower growth from July to December 2019. The subsidies for NEVs is announced to be extended to 2022 which was planned to be removed in 2021 (The State Council, 2020).

The slowdown of NEV sales mainly due to a collective purchase before the "cutdown", but also reflect a narrow space for suppliers to adjust the price in response to it at present. In contrast with other markets, small size or economy BEVs achieved price parity at the purchase stage in China. For high-end vehicle, price gap can be offset by the present tax exemption (¥33,000 for advanced PEVs). Data shows the weighted average manufacturer suggested retail price (MSRP) gap of passenger vehicles between PEVs and ICEVs is $5,000 USD before subsidies[3] in 2017 (Ou et al. 2019: data is from automotive data center database of China automotive technology and research center). The present level of subsidies supports more advanced vehicles (mainly PEVs with longer driving range) to eliminate lower quality products. Thus, price gap and technical gap between

---

[1] Plug-in electric vehicle (PEV) encompasses battery electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV).

[2] The term NEV includes BEV, PHEV, and fuel cell vehicle (FCV) in China. However, the number of FCV is very limited.

[3] The average subsidies for PEV is close to $5,000 USD before reduction.

PEVs and ICEVs should not be primary barriers to PEV uptake.

To avoid excessive subsidies, PEVs in China are categorized into officially and unofficially certified models. Only officially certified models qualify for subsidies and subsidy levels various across different products (Ou et al.2019). The Catalogues of Recommended Models for NEV Popularization and Application which release almost 12 times a year include the certified passenger BEVs and PHEVs. However, most of the indicators for technical features are theoretical numbers, and approximately 100 models are certified in each release. Without collecting information on PEVs and related policies of center and local government, it is a hard task for consumers to select an ideal vehicle. It is reasonable that social influence, knowledge of PEVs as well as environmental awareness can play an unignorable role in such a complex decision making beyond price and technical features.

These possible influential factors have been examined across abundant studies worldwide (Liao et al. 2017). However, most of the studies assume consumers are rational decision makers. Several studies reviewed the impacts of social influence, psychological factors as well as knowledge of policies. Rezvani et al. (2015) reviewed PEV adoption research and pointed out that understanding the policy is important. Pettifor et al. (2017) conducted meta-analysis on social influence on PEV uptake and found vary effects across 21 studies. They assumed these results are coming from cultural and social differentials.

Domestic studies in China paid less attention on the social influence or other psychological factors but the efficiency of policies (Wang et al. 2017; Ma et al. 2019). Most of the studies highlighted the effects of driving restriction and license number plate lottery policy. In the first-tier cities such as Beijing and Shanghai, the restriction policy and urban sprawl have pushed the purchasing of PEVs during 2010 to 2017. However, sales in these cities shared less in national EV market, approximately 40% since June 2017 (Renming Daily, 2019; WAYS, 2020). A nationwide survey which carried out in 2018, also showed residents in non-first-tier cities (42%) are more willing to buy PEVs compared to those in first-tier cities (35%) (Ming 2018). This phenomenon is driven by the remarkable growth of PEV uptake in non-license plate-controlled cities[4]. It is crucial

[4] To limit ICEV use and promote PEV uptake, cities like Beijing, Shanghai introduced license

whether social influence, environmental awareness or interest in PEV technology conducive to this diffusion.

To fill the gap, this study investigates the impacts of psychological factors on consumers' preference of PEVs in two cities with and without restrictions. Specifically, this study attempts to examine the impacts of psychological factors from three aspects. (i) social influence. Comprehend the role that social influence plays in the process of decision making is important for extending public acceptance. (ii) the knowledge of PEVs and policy incentives. The efficiency of subsidies directly depends on the propagation of knowledge both on PEVs and subsidies. It is useful to know the necessity to improve institutional capacity. (iii) attitudes/social norms ,such as environmental attitudes and innovativeness. The awareness of air pollution and car related environmental problems has been confirmed in the literature which contributes to a consumer-oriented shift towards PEV transition.

The majority of studies within this body of literature applied traditional discrete choice model to discuss the consumer preferences on vehicle attributes along with other features (Liao et al.2017). However, little is known about the attitudes or awareness to these technical features (Tanaka et al. 2014). The hybrid discrete choice model which can simultaneously estimate the effects of latent attitudes, social influence as well as technical aspects and household socioeconomic characteristics, has been applied in recent years (Kim et al. 2014; Tchetchik et al. 2020). Thus, this study constructs a hybrid choice model combined with the above latent variables and object-case best worst scaling (BWS) experiment. Object-case BWS is developed to examine the relative importance of attributes (Finna and Louviere 1992) and choice scenarios differ in subset of attributes provided. It is possible to investigate whether social influence affects preference on each functional attributes. A separate model is constructed to examine the impacts of social influence, attitudes and knowledge on WTP for PEVs.

The remainder of the paper is organized as follows: Section 2 reviews previous studies that have been conducted in China. Section 3 describes the study area and the experimental design of the BWS object-case. Section 4 presents the methods used for

plate lottery policy, which allocates a limited number of ICEVs to deal with traffic congestion as well as air pollution.

estimation. Results are presented in Section 5 and discussed in Section 6. Conclusions and policy implications are drawn in the final section.

2. Literature Review

Based on an extensive literature review of studies on PEV adoption carried out since 1970s[5], two approaches have been developed in this field, economic approach (eg. TPB and discreate choice theory) and agent-base modeling approach (Al-Alawi and Bradley, 2013; Liao et al. 2017). Because of the limitation of market data, majority of studies use stated preference (SP) surveys under the random utility theory. Factors which used to investigate the uptake intention or willingness to pay(WTP) can be grouped into situational and psychological factors (Lane and Potter 2007; Li et al. 2017). A trend is observed in the literature that concentration has been shift from situational factors such as technical attributes (e.g., Brownstone et al.2000; Axsen, Mountain and Jaccard 2009; Hoen and Koetse 2014), incentives (e.g. Tanaka et al. 2014; Zhang et al.2014; Langbroek et al.2016), socio-demographic factors (Campbell et al. 2012) to psychological factors (Rezvani et al. 2015) such as social influence (Pettifor et al. 2017), experience(Daramy-Williams et al. 2019), or regional differences comparison (Abotalebi et al. 2019). It is because generally, financial and technical attributes have been confirmed to have significant effects on PEV adoption worldwide, while social influence (Pettifor et al. 2017), experience (Jensen et al. 2013), and other psychological factors (kim et al. 2014) show more complicated impacts across the studies (Liao et al. 2017).

Table 1 summarizes studies conducted in China after 2009, the year that the government started issued financial support to promote PEVs.

---

[5] In the early stage, alternative fuel vehicle(AFV) which includes other types of vehicles. However, in recent years, BEV and PHEV are the two main types of AFVs.

Table 1 Overview of studies and results

Publication	Methodology	Location	Survey Year	Sample size	Vehicle type	Technical attributes	Social influence factors	Psychological factors	Policy incentives	Socioeconomic and demographic factors	Main comparable findings
Qian and Soopramanien (2011)	**DCE**	**Not mentioned (students take home survey)**	**2009**	**527**	**ICEV, BEV, HEV**	**Purchase price, running cost, charging facility, driving range**			**Subsidies, free parking, priority lane**	**Age, gender, family size, kids under 18, working distance, car ownership, income**	**Vehicle attributes are important. Incentives are not well informed. Car ownership, family size, gender and household income are associated with PEV uptake.**
Zhang, Yu, and Zou(2011)	**SP**	**Nanjing (restriction introduced)**	**2011**	**299**	**EV**	**Price, fuel price, fuel availability, maintenance cost, safety**	**Peers opinions**	**Knowledge on EVs (not examined for EV uptake intension)**	**Policy, tax reduction**	**Age, gender, education, income, family size, driver license owner, vehicle number, EV experience**	**Policy is not well known. Higher educated people are less likely to adopt EVs.**
Helveston et al. (2015)	**DCE**	**US/China (restriction introduced)**	**2012-2013**	**384**	**BEV, PHEV, HEV**	**Purchase price, operating cost, acceleration time, vehicle type, brand, fast charging capability**	**status symbol**	**Attitudes towards storage space, reliability, safety, towing capacity, outward appearance**		**Age, income, family size, No. of children, number of vehicles, education, gender, married, car use behavior**	**Mean WTP for technology of Chinese consumers is within $10,000 of equivalent ICEVs.**

Yang et al. (2017)	DCE	Beijing; Shanghai	2014	1264; 1152	EV				License wait time, bid price, subsidy	Age, gender, education, income, family size	Policy incentives and driving range of EV are significant to EV adoption.
Lin and Tan (2017)	CVM	First tier cities	2016	958	EV			Attitudes towards charging facilities, environmental benefit of EVs, knowledge		Age, gender, education, family size, income, car ownership	Knowledge about EVs, income, younger people, education, attitudes towards the charging facilities and car owners positively related to WTP.
Li et al.(2018)	DCE	Jiangsu Province	2016	928	EV	Purchase price, range, charging time, charging station, emissions, fuel cost			Road toll, vehicle and vessel tax, personal carbon trading	Age, gender, education, family size, income, location	Personal carbon trading effect is lower than subsidies. Policies are less important compare to some performance attributes.
Wang, Tang, and Pan (2017)	TPB	China	2014	247		Purchase price, range, charging services, inner/external performance	PEV public acceptances	Environmental awareness; innovative personality		Age, gender, education, income, car ownership, occupation, marital status	Low public acceptance of PEVs and low purchase intension was found.

She et al. (2017)	SP	Tianjing	2016	476	EV	Range, power, reliability, battery life, charging time, safety, price, battery cost, infrastructure for charging		Environmental awareness	Financial incentives, convenience policies	Age, gender, education, income, car ownership, experience, family size	Safety, reliability and range are the most important features. Increasing the density of charging infrastructure is the most preferred policy. A dense network of charging infrastructure is required.
Wang, Li and Zhao(2017)	TPB	Ten cities with restriction	2014	324	EV			Environmental concern	Financial incentives,information provision, restrictions on ICEVs	Age, gender, education, income, number of cars owned	Restrictions on ICEVs are most powerful to PEV uptake; environmental concern combined with policies could play a moderating role.
Huang and Qian (2018)	DCE	Second- and third-tier cities	2016	233; 115	ICEV, PHEV, BEV	Purchase price, operating cost, driving range, emission, brand, home charging capability, availability	Normative influence-face preservation, symbols of car-ownership	Risk aversion	Purchase subsidies, policy of vehicle licensing, driving restriction, congestion charge, access to bus lanes	Age, gender, education, car use experience, car ownership, family size, number of kids	Purchase price, subsidies and PEV charging network are important to third tier cities. Normative face influence play an important role in EV adoption.

Habich-Sobiegalla et al. (2018)	**SP**	**China, Russia, And Brazil**	**2017**	**1,078**	**EV**	**Purchase costs, technological readiness (battery life, cruising range)**	**EV owner in social network, online sharing frequency, size of online network**	**Environmental concerns**	**Initiatives**	**Age, education, gender, income, location**	**Age and education have a weak effect in China. Social influence factors have a strong influence while government policy initiatives have limited effects on purchase intention.**
Qian et al. (2019)	**DCE**	**China**	**2015**	**1,076**	**PEV**	**Purchase price, running cost, driving range, fast service station, service speed, charging speed, coverage of charging station, permission to install home charging post**			**Subsidy, licensing policy**	**Age, gender, education, income, family size, car ownership, type of cities**	**Heterogeneous preference towards PVs is found. Age, gender, lower income family associated with PV purchasing intention.**
Ma, Xu and Fan (2019)	**DCE**	**Nation wide (Mainly in Guangdong)**	**2017**	**1,719**	**EV**	**Charging time, charging station, driving range**		**Attitudes (know about EVs, environmental benefit of EVs)**	**Financial subsidies and non-financial policies**	**Age, gender, income, education, family with children, type of cities (First and second tier)**	**Recognition of the environmental benefit of EVs, gender, family with children and type of cities have significant impacts on policy preferences.**

Zhuge and Shao(2019)	**SP**	**Beijing**	**2015-2016**	**651**	**EV**	**Vehicle price**	**Influence from friends, neighbors and social media**	**Environmental awareness, driving experience**	**Purchase permit, usage constraint**	**Age, income, education, vehicle number, family size, location**	**Vehicle price and usage are most influential factors; social influence and purchase restriction also played important roles; income and education relate to preferences on technical attributes and policy incentives.**

Notes: SP, stated preference.

Studies in China show similar trend. Economic approach (Wang et al. 2017; Ma et al. 2019) is widely applied and both situational factors such as technical attributes, policy incentives, socioeconomic and demographic characteristics, and psychological factors such as social influence, environmental attitudes/social norms have been examined as well. There are two main features of these domestic studies.

First, most studies focus on policy incentives efficiency in cities with driving or plate restrictions. Policy incentives were not recognized/understood well by individuals in early studies (Zhang et al. 2011; Qian and Soopramanien 2011). With the practice of policy incentives and probably the increased availability of PEV models in the market, incentives started to play a significant role in PEV uptake (Yang et al. 2017). After 2011, more efforts were made to assess the effectiveness of various policy incentives and develop policy recommendation but mainly focus on the first and second-tier cities. For instance, She et al. (2017) tested the acceptance of 15 different types of policy incentives in a second tier city, Tianjin and found subsidies are well recognized but the density of charging infrastructure is ranked top important. Wang, Li and Zhao (2017) also found that charging infrastructure construction-related convenience policy is more important than financial incentives or information provision for customers in first and second-tier cities. Diao et al. (2016) and Ma et al. (2019) noted that policy effects are greater in megacities than second-tier cities due to the joint effects from driving and number plate restrictions. However, less studies were conducted in cities with no traffic restrictions or license plate restrictions. One exception is Huang and Qian (2018), which covered second and third-tier cities in southern Jiangsu Province, found the barriers to PEV adoption are different across regions. Individuals in third-tier cities value the government subsidies much more important than residents in second-tier cities, while other types of incentives have no effect. Ma et al. (2019) conducted a survey covered mainly first, second-tier cities but also some third-tier cities. They found common preferences among respondents from first and second-tier cities, non-financial incentives such as parking privileges can work effectively. They stated different policy combinations should be designed for first, second and third-tier cities. Moreover, Habich-Sobiegalla et al. (2018) conducted a national wide online survey in 2017 and found policy initiatives for PEVs have no significant effect on WTP.

On the other, residents' knowledge on PEVs and related subsidies directly link to the impacts of policy incentives. She et al. (2017) shown individuals are not well informed about the features of PEVs in second-tier city, Tianjin. Lin and Tan (2017) found knowledge of BEVs significantly associated with WTP in the first-tier cities. Ma et al. (2019) found knowledge (attention in their paper) positively associated with policy incentives for vehicle features rather than subsides and privileges mainly in general.

Based on literature review, it is obvious that policy incentives could have various effects on PEV uptake in cities due to various restrictions. It is reasonable to assume that those incentives also could work differently in third-tier cities. However, less evidence is obtained on whether knowledge of PEV and subsidies are different across these cities and affect PEV uptake differently in cities with and without restrictions.

Second, more and more studies contain the social influence and psychological factors. Among listed influential factors beyond policy incentives, the preferences on technical features are basically consistent, while the impacts of individual characteristics are controversial. Psychological factors might explain the variance across individuals.

In the early stage, simple interpersonal communication is tested as a measure of social influence. For instance, Zhang, Yu, and Zou (2011) stated positive effect on PEV uptake from peer group opinions in their study conducted in Nanjing. Wang et al. (2017) found family member's opinion associated with the intension of PEV adoption. To further investigate the range of influence in the local community, more systematic tests are conducted. For instance, Habich-Sobiegalla et al. (2018) examined neighborhood effect and size of online social network on PEV adoption intension and found a significant relationship. Zhuge and Shao (2019) investigated influence from friends, neighbor and social media on PEV purchase behavior in Beijing. They found social influence contributes 9.7% of PEV purchasing decision in total but these three types of social influence differ from each other.

Other studies focus on the impacts of individuals' social norms, which refer to rules or standards of behavior of referent social groups (Pettifor et al. 2017). It could be embedded in environmental concern or awareness which usually defined as psychological factor, but controversial results have been found in literature (Li et al. 2017). For instance, Wang et al. (2017) stated personal moral norm and subjective norm as well as environmental concern have limited contribution on the intention to adopt PEV. While Habich-Sobiegalla et al. (2018) found a strong and significant effects from environmental concern on purchase intentions. Ma et al. (2019) also stated respondents' awareness of the environmental benefits of PEVs significantly increase the support for incentive policies. However, there is no evidence on how social influence and psychological variables affect the preference of different functional attributes as well as the possible various impacts across different cities.

Experience and Innovativeness are also psychological factors that have been considered as major determinants of the PEV adoption ((Kim et al. 2014; Tchetchik et al. 2020; Daramy-Williams et al. 2019). Experience can be categorized into two groups: practical experience and knowledge of PEVs (Li et al. 2017). Zhang, Yu and Zou(2011) investigated the awareness of PEVs and found individuals recognize PEV as an environmental friendly products but less informed by its technical features. Lin and Tan (2017) found the belief in PEVs' contribution to air quality/knowledge on EVs is highly related to WTP. No practical experience or innovativeness have been tested as well as the differences across cities in domestic studies.

Therefore, this study focuses on the impacts from social influence, knowledge of PEVs and policy incentives, green attitudes and innovativeness on attributes' preferences as well as heterogeneity across cities with and without restrictions.

3. Conceptual framework and research hypotheses

This study aims at clarifying the impacts of psychological factors on consumer preferences of PEV attributes, such as purchasing costs, usage costs, technological readiness, air pollution reduction, CO_2 emission reduction across cities in China. Figure 1 summarize the conceptual framework of this study.

(i) Knowledge

As aforementioned, whether PEV and subsidies related knowledge fully understood by the demand side is critical for consumers to consider PEV uptake. Previous studies show consumers are not well informed in first and second tier cities (Zhang et al. 2011; Wang et al. 2017). These studies are carried out in year 2009 and 2014, the situation might be changed in cities with restriction after 10 years practice of subsidies. However, for consumers in free purchase cities, understanding the PEV and subsidies may still not well motivated. It is due to the complicacy of policy incentives and the existence of a vast numbers of technologically lower but cheaper PEVs in the market. It is difficult for consumers who have limited knowledge on vehicles to follow and distinguish the models that listed in the catalogue.

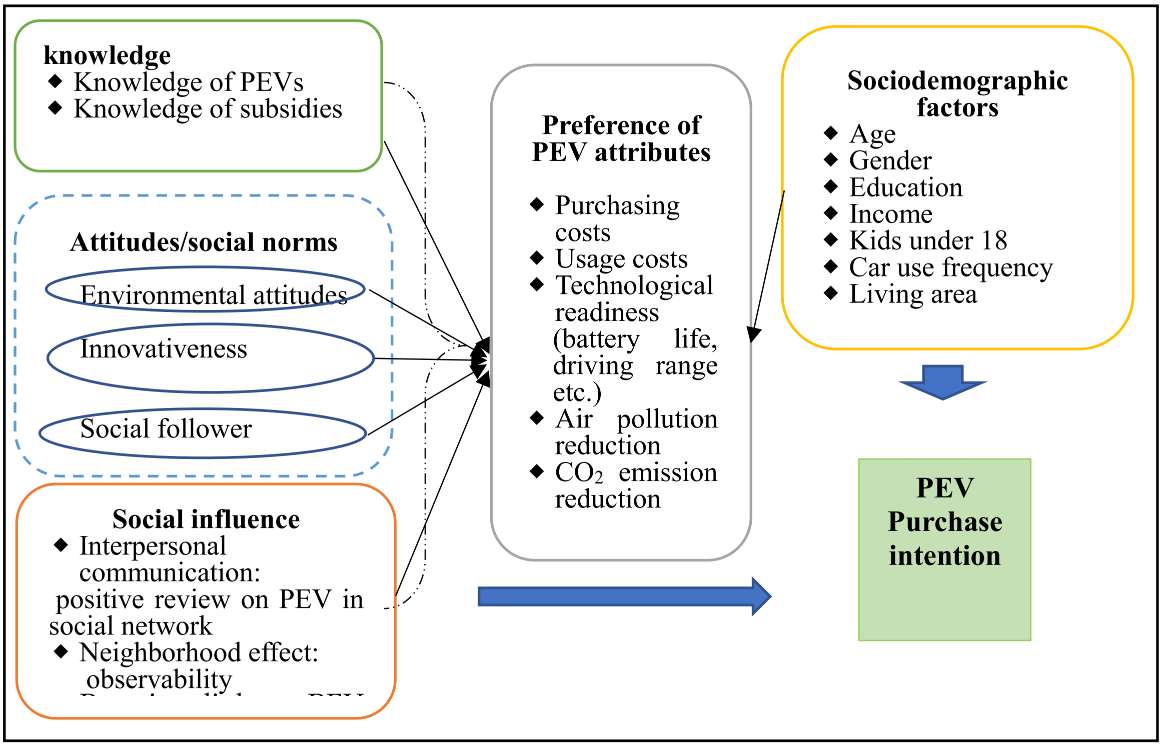

Fig. 1. Study framework

Consumers in cities with restrictions have to search knowledge of PEVs and subsidies. In contrast, consumers in cities without restrictions may feel a privilege of purchasing ICEVs compare to people in large cities. Thus, *the first group of hypotheses is*

H1-1: *Knowledge about PEVs and policy incentives* positively associated with WTP for a PEV, but the degree may different in cities with and without restrictions.

With more knowledge on PEV and related subsidies, consumers may less worried about the purchase price or technological readiness, because the price gap is low with subsidies and technological level of certified models has been improved a lot in recent years.

H1-2: *Knowledge about PEVs and policy incentives* positively associated with preferences of PEV features.

(ii) Attitudes/ social norms

As shown in Fig.1, there are two latent variables constructed for capturing the impacts of psychological factors: *environmental attitudes and innovativeness*. Environmental attitudes or awareness have been examined and showed positive impacts on purchase intension in previous studies. It is reasonable because consumers in cities with restrictions may worry about pollution from dense roads in the city area and more general environmental related practice are primarily conducted in these cities. While in cities without restrictions, people might pay less attention on environmental issue but more on urban development related issues.

Thus, *the second hypothesis is*

H2: The more agreement there is on environmental social norms, the higher the likelihood that he/she pays a higher price for a PEV across cities with and without restrictions, but the degree of impacts may different in cities with and without restrictions.

Innovativeness refers to the extent to which a person is interested and earlier in the uptake of innovative products. It has not been tested in previous studies in China probably because of the presumption that a collective culture could not form a significant market share from technology-oriented purchase. However, Habich-Sobiegalla et al.(2018) discussed the possibility of the impacts from innovativeness based on the relationship of online activities and purchase intension. Thus, *the third hypothesis is:*

H3-1: Innovativeness is positively associated with WTP, and the degree of impacts might be different across cities with restriction and without restriction.

H3-2: Innovativeness can contribute to preferences on PEV attributes, but less related to technical readiness.

(iii) Social Influence

Social influence such as observability (Mau et al. 2008; Havich-Sobiegalla et al. 2018), reviews of peers (Zhang et al. 2011; Kim et al. 2014) have been found consistently contributing to PEV adoption within and outside of China but the effect size are controversy. However, there is less evidence on the effects of social influence across different types of cities. This study examines social influence from two dimensions:

interpersonal communication and neighborhood effects. Observability, which is number of PEVs owners observed in neighborhood, is also included. In cities with number plate restriction, consumers may collect reputations of PEVs and observe the PEV users' behavior due to relatively inelastic demand for PEVs on their own initiative. In addition, social follower is also generated to examine the potential of social influence in these cities.

Thus, the fourth group of hypothesis are shown below:

H4-1: Interpersonal communication, neighborhood effects, and social followers, positively related to technical features of PEVs in city with restrictions.

H4-2: The more positive review a person received is, the higher the likelihood of he/she pay a higher price for a PEV in city with restriction but less effective in city without restriction.

H4-3: If a person observes others driving PEVs, the likelihood of he/she willing to pay for a PEV would be higher.

4. Survey design

4.1 Study area

Two cities in eastern China are selected as study areas. One is a second-tier city, Hangzhou locates in Zhejiang Province and the other is a third-tier city, Linyi in Shandong Province.

Zhejiang and Shandong Province are two provinces without first-tier cities but ranked in the top of the accumulative PEV sales in China in 2011-2017(Ou et al. 2019; and Zhang et al. 2020). Both regions are well motivated to deal with air pollution and have better financial capacities. Hangzhou with a population of 3.91 million in the main districts and an average density of 1,034 inhabitants per square kilometer by 2018, have introduced driving restrictions in the old city center during the weekdays and license plate control since year 2014. The number of family car owned per 100 urban households in Hangzhou was 0.60 in 2018 (Hangzhou Statistic Yearbook, 2019). The per capita annual disposable income in urban areas is approximately 61,172RMB (≈$9,012 USD). One urban household can afford to purchase an average priced vehicle.

Linyi city does not introduce any restrictions though its air quality is poor due to high industry density and large coal-centered energy structure. For instance, the NO_2

concentration was 45 μg/m^3, the annual PM10 concentration was 114 μg/m^3 and the PM2.5 concentration was 60 μg/m^3 in year 2018. This situation may positively affect consumers who are aware of the problem and further higher the probability of PEV uptake.

An approximate calculation was performed by the authors due to limited information; per capita vehicle ownership in Linyi was 0.18 in 2018 (the number of private passenger vehicles 1,965,044, divide by population 10.62 million, using Linyi Statistic Yearbook, 2019). If the household level (use 2.8 persons as average urban household size, National Bureau of Statistics of China) is considered, approximately 51.7% of the households own a car. This number is much higher than the national level (37.5% in urban area, China Statistic Yearbook 2018; 40% in year 2018, MPS, 2018) and it accounts for 1% of the total private vehicle ownership in China (calculated by the authors). This number is reasonable for a city with a relatively low population density, which is 614 persons per square km and with no license plate control, though its annual disposable income per capita is still low (approximately 23,528 RMB≈3,466.1$USD, 1$USD=6.788RMB in January, source: IMF Representative Exchange Rates for Selected Currencies). However, the per capita disposable income in urban areas which is 33,266RMB (≈4,901$USD), is 2.6 times than that in rural areas (which is 12,613 RMB ≈1,858.1$USD). Upper-income urban households can afford to purchase an average priced vehicle.

Based on the above aspects, the sample framework is households in the urban area of Hangzhou and Linyi.

4.2.Best-worst scaling experiment

A simple object-case BWS is designed to grasp the priority across the attributes from heterogeneous consumers.

Attributes Selection

The alternative attributes used in this study were chosen based on a literature review and an earlier pilot online survey. Table 2 summarizes the eleven attributes selected for the BWS object-case experiment. First, for vehicle features, Liao, Molin and Wee (2017) reviewed the factors accounting for heterogeneous PEV preferences. Based on their review, purchase costs, usage costs, driving range, charging time, and charging availability are the major barriers for PEV adoption. This study includes all these five attributes and added two environmental attributes, reliability, policy incentive and social imagine attribute. Environmental attributes of PEVs are rarely examined in domestic studies but widely argued in global studies. This paper adds air pollution reduction and CO_2 emission reduction as environmental attributes of PEVs. Reliability/safety[6] is also an important feature when purchasing vehicles but relatively less examined in literature (Zhang et al., 2011; Greene et al., 2018). It is probably because many studies investigate the brand preference which overlapped with reliability. As aforementioned, various policy incentives, financial policies such as reducing purchase tax (Tanaka et al., 2014) or road tax (Hoen and Koetse 2014), privileges for those using PEVs, such as free parking (Qian and Sooprammanien 2011), and open access to high-occupancy vehicle/express/bus lane (Ma, Xu and Fan, 2019) have been tested. However, in most non-first tier cities, parking fee are low and express/bus lanes are very rare. Thus, financial incentive only is included in the BWS choice sets.

The social imagine attribute is the reaction of people in social network to PEV uptake. This is different with the other social influence variables introduced in the previous sector. There are different types of PEVs in domestic market. For instance, in Linyi, there are smaller PEVs running in the city while no such PEVs can be found in provincial capital cities such as Hangzhou. Respondents who rank this object as important attribute means they are care about how other people view their purchasing behavior. In other word, they think private cars as symbolic goods.

Table 2 Attributes used in the BWS object-case experiment

No.	Attributes	Description
1	Purchasing cost	Purchasing cost is the initial cost happened when purchase an equivalent standard PEV
2	Driving range	Average driving range of an PEV
3	Usage costs	Operation cost, insurance fee are included
4	Incentives	Tax exemption, subsidies are included

[6] In the literature, safety refers to the air bag quality; however, the nuance of safety in Chinese is close to reliability.

5	charging availability	Density of charging station
6	Reliability	Safety of using an PEV
7	Air pollution reduction	The contribution of PEV to air pollutes reduction
8	Charging time	Time to charge battery
9	Battery quality	Quality of battery
10	Carbon emission reduction	The contribution of PEV to CO_2 emission reduction
11	Reaction of close social ties	The reaction of people see you drive a PEV

Questionnaire Design

The questionnaire was constructed including three parts. The first part includes knowledge of PEVs and policy incentives, social influence and attitudes/social norms related questions. The second part is the BWS experiment. A balanced incomplete block design (BIBD) was used to construct the choice sets.

Figure 2 is an example of a BWS task. Each respondent is required to finish eleven BWS tasks; in each task, there are 5 different attributes of PEVs, which were explained in the previous section. Each item appears five times in the whole experiment, and each pair cooccurs twice across the 11 sets. As shown in Figure 2, respondents were asked to check one item among the five attributes as the most important item and check another item as the least important one in this BWS choice task.

	Purchase Cost	Driving Range	Charging Time	Charging Availability	Subsidies
The most important item is	✓				
The least important item is				✓	

Figure 2 Example of a BWS task

The explanations of each attribute are provided with choice task.

The third part contains WTP related questions and socio-demographic questions. An anchored payment card is adopted for assessing individuals' WTP[7]. The question used to determine WTP is as follows: "How much are you willing to spend to buy a PEV in the next two years?" The third part contains social demographic questions such as age, gender, education, annual household income, number of children under 18, occupation, and car ownership, car use frequency, expected types of incentives, and living area (Hangzhou only[8]).

4.3.Survey details

After the pretests held in October 2018, the main surveys were conducted through the use of multistage sampling from Linyi urban households in January and July, and main districts inhabitants in Hangzhou in September 2019. Sample size is decided based on the WTP question. It is because CVM usually require larger sample size compare to choice experiment. 385 samples are necessary at the level of 95% confidence interval, with 3% of margin of error when the coefficient of variance is 3 for each city. Samples are randomly drawn from Lanshan-District, Hedong-District and Luozhuang-District in Linyi, and Bingjiang-District, Jianggan-District, and Xihu-District in Hangzhou, based on their population shares. In each district, blocks and communities were randomly selected through simple random sampling method.

Both surveys were carried out through face-to-face interviews. 50 students were trained to conduct the surveys. Individuals who were over the age of 20 and below 65, were required to answer as the household representative. For those who completed the questionnaire, a bonus reward was provided. A total of 118(winter) and 333(summer) questionnaires were received from Linyi, among them, 380 cases are valid for analysis (valid response rate=84.2%). 540 questionnaires were sent out in Hangzhou, and 483 were obtained. 21 cases were deleted due to inconsistency in questionnaire or logistical problems, 462 cases are valid for the first part, 436 cases are valid for BWS (valid response rate=80.7%).

---

[7] There are several methods that can be used to assess WTP, but because the BWS experiment covers a large part of the questionnaire, a relatively simple payment card method was applied. The options regarding the payment card were pretested

[8] There are areas with and without driving restriction in Hangzhou.

5. Econometric model

The random utility theory is usually applied in this field which assume a rational individual select best object and worst object to maximize her utility (McFadden, 1973). In practical, sequential best-worst model (Rigby et al. 2015) and maximum difference model (max-diff or paired model) (Flynn and Marley 2014) are the major models applied for investigating individual's preference. The sequential best-worst model assumes that respondents chose the best item first and then select the worst, or in reverse order, while max-diff model assumes the respondents select the best and worst items simultaneously. It is more plausible to apply sequential best-worst model for this study since most of the respondents choose the best first and then the worst.

Equation (1) gives the utility of best and worst choice for eleven sets.

$$\boldsymbol{U_{diff}^{njt} = D_{jt}\beta_{attributes} + \frac{1}{\alpha_n}\varepsilon_{njt}} \quad \textbf{(1)}$$

Where D_{bnjt} is a vector of the observed attributes, and $\boldsymbol{\beta_{attributes}}$ is a corresponding vector of the coefficients. For choice *t*, the attribute selected as the most important had its variable D taking value of 1, and that chosen as the least important taking value of minus 1. The role of scale in utility can be denoted as α_n, which switches the vector $\boldsymbol{\beta}$ in magnitude dependency on the influence of included factors on respondents' choices (Hess and Train, 2017). The scale parameter usually set to 1 in multinomial logit model(MNL). The error term ε, follows a type I extreme value IID distribution.

$$P_{njt} = \frac{exp^{\frac{[D\beta]}{\alpha}}}{\sum_j^J exp^{\frac{[D\boldsymbol{\beta}]}{\alpha}}} \quad \textbf{(2)}$$

Because the choice of attributes could be different across individuals, D also includes alternative-specific variables. The probability that individual *n* chooses alternative *n* from *j* set is given by Equation 3.

However, unobserved preference heterogeneity and heterogeneity in error variance must be examined through other models. A mixed logit model (MXL), which avoids the property of the independence of irrelevant alternatives (IIA) of a multinomial logit, is developed (McFadden and Train, 2000) and widely applied for this purpose (Dubé et al., 2002). This model allows the utility coefficients to differ across respondents, using $\beta_n^{'}$. To further check the heteroscedastic error variance, a heteroscedastic conditional logit model is used for robust test.

6. Results

Sample characteristics

The main descriptive statistics for respondents' social demographic characteristics are shown in Table 3. Z/T-tests were conducted for testing the differences between two cities. The results show significant differences of kids under 18(kids 18)(P value=0.004), car use frequency(P value=0.007) across the two datasets. Men are more cooperative to take the survey in both cities. 33.84% in Linyi and 60.13% in Hangzhou had an academic degree (years of schooling larger than 16). The majority were aged between 30 and 49 years old (67% in Linyi and 60% in Hangzhou) and employed or self-employed (90% in Linyi and 91% in Hangzhou)[9]. The mean annual income per household is approximately 164,319RMB(≈17,117 $USD) in Linyi, and the standard deviation(SD) is 175,519RMB. Thus the 95% confidence interval is [146,237RMB, 182,400RMB], much higher than data from Statistic Yearbook(=99,798RMB per household[10]). The mean household income from Hangzhou sample is 279,097RMB, the 95% CI is [259,405RMB, 298,790RMB], also higher than the results from the Statistic Yearbook (=183,516RMB per household). This finding indicates that households with higher income or larger family size were more cooperative to join in taking this vehicle-related survey, while lower-income families may have no plan for purchase a vehicle and refused to take the survey. The percentage of car ownership in the sample is 80.11% in Linyi and 78.57% in Hangzhou (95% confidence interval: [76.03%, 84.18%], n=372 in Linyi; [74.70%, 82.45%], n=434 in Hangzhou). These results are again higher than the Statistic Yearbook which is reasonable, the probability of owning a vehicle is higher if the family income is high.

Table 3 Descriptive analysis for demographic variables

Variable	Description	Linyi	Hangzhou

[9] College students without income are not included.
[10] Here we assume the household size is three persons.

		Mean	SD	Mean	SD
Age	Linyi: from 18 to 65; Hangzhou: from 18 to 84	34.19	8.54	36.83	11.20
Gender	Male=1	57%		54%	
Income	Seven categories for income, range from \30 to \1,000- or above. Unit=thousands RMB	164.3	176	279.1	205.6
Education	Years of schooling	14.07	2.84	15.13	2.54
Household size	Not collected in Linyi			3.54	1.22
Kids 18	Children below 18 years old=1	66%		57%	
Car ownership	Own a car=1	80%		79%	
Car use frequency	Logged car use frequency in a year (based on days)	5.00	1.45	4.71	1.87

Note: number of cases are different for each variable. Occupation is omitted from this table.

Knowledge and Social Influence

Knowledge and social influence related variables are summarized in Table 4. Whether respondents know the definition of PEVs is asked. T-tests and Kruskal-Wallis equality of populations rank tests are applied for examining the difference across two samples. *Knowledges of PEVs*(chi2(1)=4.930, P=0.026) and *subsidies* (chi2(1)=22.495, P=0.000) are statistically significant between two samples. While *interpersonal communication* (chi2(1)=0.424, P=0.515), *neighborhood effect*(t-value=*-0.382, P*=0.703) and *observability* (chi2(1)=0.021, P=0.885) show no difference across two samples.

Table 4 Descriptive analysis for information and social influence variables

Factor	Variable name	Description	Linyi	Hangzhou
Information	◆ Knowledge of PEVs	"=1" if respondent know the definition of PEVs in China	18.79%	26.51%

	◆ Knowledge of subsidies	"=-1" if respondent had never heard about the subsidies	34.94%	17.17%
		"=0" if respondent knew subsidies for PEVs	57.53%	70.22%
		"=1" if respondent did researches on subsidies for PEVs	7.53%	12.61%
Social influence	◆ Interpersonal communication	"=-1" if negative reviews shared more on PEVs in respondent's social network	21.17%	17.14%
		"=0" if neutral reviews shared more on PEVs	46.01%	45.55%
		"=1" if positive reviews shared more on PEV in social network	32.82%	37.31%
	◆ Neighborhood effect	"=1" if respondent observe people adopt PEV in close social network	43.77%	44.96%
	◆ Observability	Observability (no one)	65.64%	54.33%
		Observability (≦5)	31.79%	22.51%
		Observability (> 5)	2.56%	23.16%

WTP

Approximately 94%(Linyi) and 92%(Hangzhou) of the two samples were willing to pay for a PEV, which is relatively high. Mean WTP of Linyi sample is133,690RMB, with SD 69,645.95RMB, and mean WTP of Hangzhou sample is 197,586RMB, with SD 107,615.70RMB. T-test suggests statistically significant difference of WTP across these two samples (t=-10.155, df=752, P=0.000).

Confirmatory factor analysis (CFA)

Attitudes and social norms are collected based on the theory developed in this field (Wang et al. 2017) through Likert type scale questions from “strongly disagree” to “strongly agree”. CFA has been widely used for determining factorial validity of this instrument construction. The descriptive analysis and intercorrelations for attitudes, social norms items are shown in Table 5. Because of the skewness of the responses, the maximum likelihood (ML) which assumes the observed variables follow a continuous and multivariate normal distribution, is not appropriate for this ordinal dataset.Recent studies have suggested weighted least squares with mean and variance adjustment (WLSMV) is superior to ML when ordinal data are used (Li 2016). The analysis was conducted using R (lavaan) which can generate a polychronic correlation matrix applying WLSMV. Each latent factor is standardized. Omega coefficients and average variance extracted (AVE) were obtained based on the original variables, while ordinal alpha coefficients were calculated from the polychronic correlation matrix. The ordinal alpha was introduced by Zumbo, Gadermann, and Zeisser (2007) and have been accepted as a better reliability coefficient than Cronbach's alpha in the literature (Yang and Green 2011; Gadermann, Guhn, and Zumbo 2012).

Table 5 Intercorrelations, Means, Standard Deviation, Skewness and Kurtosis for Attitudes Items (Hangzhou above and Linyi below)

	Hangzhou	**Mean**	**S.D.**	**Min**	**Max**	**S**	**K**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1	ENVI	0.998	0.840	-2	2	-1.096	4.804	1							
2	ENVII	1.065	0.802	-2	2	-1.004	4.729	0.861	1						
3	ENVIII	1.527	0.673	-2	2	-2.191	11.243	0.527	0.596	1					
4	ENVIV	1.028	0.726	-2	2	-0.950	5.337	0.487	0.518	0.395	1				
5	SCOI	0.247	0.850	-2	2	-0.335	3.039	0.309	0.355	0.135	0.248	1			
6	SCOII	0.251	0.955	-2	2	-0.179	2.536	0.261	0.327	0.203	0.285	0.548	1		
7	INNOVI	0.106	0.987	-2	2	0.002	2.575	0.041	0.079	0.036	0.104	0.266	0.189	1	
8	INNOVII	0.425	0.984	-2	2	-0.374	2.798	0.018	0.067	0.032	0.032	0.188	0.149	0.500	1

	Item	Mean	S.D.	Min	Max	S	K	0	1	2	3	4	5	6
0	ENV0	1.119	0.958	-2	2	-1.310	4.735	1						

1	ENVI	1.250	0.773	-2	2	-1.016	4.316	0.597	1					
2	ENVII	1.225	0.763	-2	2	-0.984	4.589	0.478	0.721	1				
3	ENVIII	1.670	0.581	-2	2	-2.067	8.916	0.531	0.544	0.521	1			
4	ENVV	1.295	0.803	-2	2	-1.107	4.176	0.465	0.561	0.462	0.604	1		
5	INNOVII	0.367	1.069	-2	2	-0.221	2.421	0.260	0.342	0.376	0.357	0.409	1	
6	INNOVIII	0.372	1.120	-2	2	-0.236	2.286	0.229	0.177	0.093	0.225	0.406	0.510	1

Note. S=skewness; K=kurtosis. Polychoric correlations are shown in the tables. Item ENVIV and INNOVI are not used in Linyi analysis due to low AVEs.

The CFA output of the measurement model is shown in Table 6 (Hangzhou) and Table 7 (Linyi). There are several items were dropped from the final analysis due to low reliability.

Table 6 CFA analysis for Hangzhou

Factor	Item	Factor loading		S.E.	Omega	AVE	Alpha
Environmental attitudes					0.819	0.557	0.838
	ENVI	0.876	***	0.002			
	ENVII	0.979	***	0.002			
	ENVIII	0.608	***	0.003			
	ENVIV	0.572	***	0.004			
Social Followers					0.652	0.483	0.710
	SCOI	0.778	***	0.005			
	SCOII	0.707	***	0.005			
Innovativeness					0.615	0.484	0.660
	INNOVI	0.841	***	0.01			
	INNOVII	0.588	***	0.008			
Total					0.800	0.510	0.750

Note. Cases =424 (based on valid cases for BWS), CFI=0.997, TLI=0.996, RMSEA=0.045, SRMR=0.031.

Table 7 CFA analysis of Linyi sample

Factor	Item	Factor loading		S.E.	Omega	AVE	Alpha
Environmental attitudes					0.747	0.432	0.829
	ENV0	0.668	***	0.003			
	ENVI	0.923	***	0.002			

	ENVII	0.763	***	0.003			
	ENVV	0.627	***	0.004			
Innovativeness					0.642	0.476	0.675
	INNOVII	0.782	***	0.009			
	INNOVIII	0.661	***	0.008			
Total					0.739	0.452	0.76

Note. Cases =371, CFI=0.996, TLI=0.992, RMSEA=0.056, SRMR=0.031.

BWS Aggregated results

The BWS standardized scores of each attribute from the two city samples are shown in Table 8. The standardized BWS scores are BWS scores(B-W) divided by the total number of occurrences of the attributes, adjusted for the sample size, which scales the BWS scores between -1 and 1. BWS scores is gained by best score minus worst score, where best score is the sum of selections of a given attribute considered as the best (most important) attributes in all tasks, and worst score is the sum of selections for a given attribute considered as the worst (least important) attributes in all tasks. Based on the results, reliability, battery quality and driving range are the largest barriers to PEV adoption, while attitudes around, CO_2 emission reduction and policy incentives are ranked as the least important features when making the decision to purchase PEVs. This result is consistent with the summary of Liao et al. (2019). Two-sample Wilcoxon rank-sum test is applied to examine the difference across two samples. The ranks sum are 126 (Linyi) 127 (Hangzhou). The rank difference across two samples is not statistically significant (z=0.033, P=0.974), which indicates people have similar taste regard with importance of these features in general.

Table 8 The standard BWS scores and ranks of attributes in two cities

Attributes	Hangzhou	Rank (HZ)	Linyi	Rank (LY)
Purchasing cost	0.037	5	0.051	5

Reactions	-0.761	11	-0.769	11
Driving range	0.253	2	0.213	3
Charging time	-0.084	8	-0.112	8
Charging infrastructure	0.034	6	0.04	6
Reliability	0.633	1	0.613	1
Air pollution reduction	-0.082	7	-0.068	7
CO2 emission reduction	-0.142	9	-0.178	10
Incentives	-0.148	10	-0.173	9
Battery quality	0.194	3	0.282	2
Usage costs	0.066	4	0.102	4

Model estimation results

Mixed logit models were constructed using two samples separately. Statistical software R is used ("Mlogit" package). The estimation started with basic models that include main effects only. Models which based on Reaction of PEV purchasing or Battery quality received lowest Akaike Information Criterion(AIC), and the standard deviations of parameters are significant which show heterogeneities across respondents. However, comparing different preferences base on purchase price of PEVs can provide more useful information for decision makers since low-price strategy is not sustainable in most of the cases. The results of purchasing costs-based basic model indicate that driving range, charging time, usage costs, battery quality and reliability are random parameters in both models, while air pollution reduction also shown as random parameter in Hangzhou model. It means that respondents' preferences across these attributes are various. Sociodemographic variables, knowledge, social influence variables and latent attitudes are included step by step in the models. Gender, age, years of schooling, car use frequency, and household income are added in the models, while kids under 18, car ownership, and PEV experience are dropped from the models.

Results of two sets of models are shown in Table 9 and Table 10. To save space, sociodemographic variables are omitted from the tables and report the results here. First, for socioeconomic characteristics, driving range is found to be more preferred by male (around 0.215*** in Linyi model and 0.412*** in Hangzhou model). Years of schooling associated with preference of reactions (0.108* in Linyi model and 0.058* in Hangzhou model). Household income is related with preference of charging time (0.059* in Linyi model and 0.077* in Hangzhou model), which is reasonable that higher time value for higher income poeple. Differences between two samples are also found. The probability for male to choose air pollution and CO_2 emission reduction (positive in Linyi model and non-significant in Hangzhou model), and the probability of frequent car users to choose battery quality as important attribute (positive in Linyi sample and negative in Hangzhou sample) are different across two samples.

Second, knowledge of PEVs and policy/subsidies show different trend across two samples.The coefficient of *Knowledge of PEVs* is positively associated with preference on charging time in Linyi model. However, it is negatively associated with preferences on air pollution and CO_2 reduction in Hangzhou model. *Knowledge of policy*, positively affects preference on charging infrastructure and usage costs in Linyi model but negatively affects on reliability and incentives in Hangzhou model. These results probably reflect worries of Linyi respondents on charging infrastructure and usage costs comparing with purchase costs, while respondents in Hangzhou do not expect higher subsidies.

Third, three social influence measurements suggest various impacts exist across two samples. *Interpersonal communication* positively affects the preferences of charging infrastructure and reliability in Linyi model, indicating that people are less satisfied with charging infrastructure and reliability of PEVs in Linyi. It is negatively impacts on preferences of air pollution and CO_2 reduction in all models. *Neighborhood effects* also show different trend across two samples. The coefficient of neighborhood effects is negatively associated with charging time in Linyi model, but positively related with driving range in Hangzhou model. These results suggest that charging time might not be considered as a serious problem in Linyi, while in a larger city such as Hangzhou, neighborhood effects cannot reduce the worries on charging time of PEVs.

Fourth, the coefficients of *environmental awareness* are negative and non-significant except for CO_2 emission reduction and reliability (Hangzhou model only). It may be due to the relative advantages of PEVs compares to ICEVs in CO_2 emission reduction comparing to the preference on purchase costs. *Innovativeness* negatively affects the preferences on charging infrastructure and reliability in both samples, and positively impacts on CO_2 emission and air pollution reduction only in Hangzhou model. This may suggest those who are inclined to innovations less worried about infrastructure and reliability, but they are slightly different across two samples. Respondents with innovative awareness in Hangzhou are innovative environmentalists and list CO_2 emission function as important attributes when choosing PEVs, while those in Linyi are less environmental sensitive.

The social followers related to environmental issue

This latent variable only examined in Hangzhou. Its coefficients are positively associated with air pollution reduction but not CO_2 emission reduction, which indicates respondents realize PEVs can contribute to clean air but may doubt about the CO_2 emission reduction function. It also related to reactions of PEV uptake among strong ties significantly but negatively. Those who would like to follow the majority are not care about people's reaction on his/her purchasing behavior. It indicates that people who would like to follow others do not think PEV as symbolic goods but more collectivism-oriented behavior. Thus, social followers do not care about driving range and reliability of PEVs either.

The SD of parameters of reliability, battery quality and usage costs remain significant, indicating heterogeneity of these preferences in Linyi respondents. However, the SD of parameters in Hangzhou model are no longer significant which indicates less heterogeneous preferences when based on purchasing costs.

Table 9 Mixed logit results of Linyi sample

Variables	Model 1			Model 2			Model 3			Model 4		
	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.
Reactions												
ASC	-2.124	***	0.275	-2.001	***	0.286	-1.993	***	0.139	-1.984	***	0.220
Knowledge of PEVs	-0.016		0.021	-0.015		0.021	-0.015		0.020	-0.019		0.022
Knowledge of policy	0.083		0.155	0.085		0.156	0.092		0.155	0.088		0.155
Detailed knowledge of policy	-0.055		0.274	-0.052		0.275	-0.045		0.275	-0.047		0.275
Postive opinions on PEVs	0.120		0.098	0.121		0.098	0.115		0.099	0.116		0.099
Neighborhood effect				-0.010		0.141	-0.019		0.141	-0.013		0.141
Environmental attitudes							0.030		0.077			
Innovativeness										0.027		0.061
SD	0.172		1.965	0.180		1.992	0.034		2.739	0.105		2.399
Driving range												
ASC	1.106	***	0.090	1.095	***	0.083	1.095	***	0.083	1.099	***	0.083
Knowledge of PEVs	0.014		0.018	0.010		0.018	0.009		0.018	0.024		0.019
Knowledge of policy	0.070		0.132	0.097		0.131	0.080		0.131	0.076		0.131
Detailed knowledge of policy	0.532	*	0.258	0.581	*	0.256	0.568	*	0.256	0.538	*	0.256
Postive opinions on PEVs	-0.051		0.084	-0.035		0.082	-0.013		0.083	-0.002		0.084
Neighborhood effect				-0.215		0.121	-0.198		0.122	-0.194		0.121
Environmental attitudes							-0.103		0.067			
Innovativeness										-0.119	*	0.049
SD	0.360		0.742	0.226		0.994	0.234		0.966	0.251		0.917
Charging time												
ASC	0.109		0.080	0.114		0.080	0.114		0.079	0.113		0.080
Knowledge of PEVs	0.048	*	0.020	0.045	*	0.019	0.044	*	0.019	0.072	***	0.021
Knowledge of policy	-0.013		0.145	0.023		0.140	0.011		0.141	-0.004		0.140
Detailed knowledge of policy	-0.081		0.288	-0.023		0.281	-0.032		0.281	-0.071		0.281
Postive opinions on PEVs	0.051		0.091	0.069		0.088	0.083		0.089	0.117		0.089
Neighborhood effect				-0.273	*	0.131	-0.262	*	0.131	-0.245	#	0.130
Environmental attitudes							-0.070		0.072			
Innovativeness										-0.179	**	0.058
SD	0.769		0.407	0.549		0.510	0.546		0.507	0.520		0.530
Charging infrastructure												
ASC	0.615	***	0.064	0.618	***	0.064	0.619	***	0.064	0.620	***	0.064
Knowledge of PEVs	0.031		0.019	0.030		0.020	0.030		0.020	0.052	*	0.023
Knowledge of policy	0.380	**	0.137	0.390	**	0.137	0.387	**	0.138	0.369	**	0.138
Detailed knowledge of policy	0.389		0.267	0.406		0.268	0.400		0.269	0.363		0.270
Postive opinions on PEVs	0.240	**	0.090	0.245	**	0.089	0.250	**	0.090	0.287	**	0.092
Neighborhood effect				-0.074		0.126	-0.070		0.127	-0.037		0.126
Environmental attitudes							-0.024		0.073			
Innovativeness										-0.156	**	0.056
SD	0.069		1.440	0.073		1.549	0.083		1.530	0.124		1.410
Reliability												
ASC	2.791	***	0.302	2.609	***	0.217	2.609	***	0.217	2.587	***	0.210
Knowledge of PEVs	0.008		0.023	0.007		0.019	0.007		0.019	0.007		0.019
Knowledge of policy	0.126		0.179	0.134		0.149	0.131		0.150	0.132		0.146
Detailed knowledge of policy	0.279		0.353	0.314		0.296	0.310		0.296	0.309		0.291
Postive opinions on PEVs	0.251	*	0.120	0.239	*	0.099	0.243	*	0.100	0.240	*	0.099
Neighborhood effect				-0.137		0.140	-0.134		0.141	-0.136		0.137
Environmental attitudes							-0.020		0.077			
Innovativeness										0.004		0.053
SD	1.780	***	0.426	1.002	**	0.374	0.999	**	0.374	0.914	*	0.380

Variables	Model 1 Coef.		Model 1 S.E.	Model 2 Coef.		Model 2 S.E.	Model 3 Coef.		Model 3 S.E.	Model 4 Coef.		Model 4 S.E.
Air pollution reduction												
ASC	0.219	**	0.070	0.221	**	0.068	0.221	**	0.068	0.220	**	0.068
Knowledge of PEVs	-0.006		0.020	-0.009		0.020	-0.009		0.020	-0.009		0.020
Knowledge of policy	0.030		0.146	0.041		0.146	0.025		0.146	0.038		0.146
Detailed knowledge of policy	0.413		0.264	0.449	#	0.264	0.436	#	0.265	0.443	#	0.265
Postive opinions on PEVs	-0.200	*	0.093	-0.197	*	0.093	-0.177	#	0.094	-0.197	*	0.095
Neighborhood effect				-0.114		0.132	-0.096		0.132	-0.109		0.132
Environmental attitudes							-0.099		0.074			
Innovativeness										0.003		0.054
SD	-0.144		0.910	-0.058		1.006	-0.062		1.008	-0.041		1.017
CO2 emission reduction												
ASC	-0.262	***	0.075	-0.256	***	0.074	-0.257	***	0.074	-0.255	***	0.075
Knowledge of PEVs	-0.008		0.020	-0.012		0.020	-0.012		0.020	-0.003		0.021
Knowledge of policy	-0.088		0.140	-0.060		0.140	-0.084		0.141	-0.075		0.140
Detailed knowledge of policy	-0.043		0.270	0.016		0.270	-0.003		0.270	-0.012		0.271
Postive opinions on PEVs	-0.266	**	0.090	-0.254	**	0.090	-0.221	*	0.091	-0.230	*	0.091
Neighborhood effect				-0.211		0.128	-0.180		0.129	-0.196		0.129
Environmental attitudes							-0.161	*	0.073			
Innovativeness							0.109		0.816	-0.081		0.052
SD	0.132		0.772	0.108		0.818				0.108		0.819
Incentives												
ASC	-0.229	**	0.070	-0.235	***	0.069	-0.235	***	0.069	-0.233	***	0.069
Knowledge of PEVs	0.016		0.019	0.016		0.019	0.015		0.019	0.017		0.020
Knowledge of policy	0.040		0.136	0.032		0.136	0.016		0.136	0.029		0.136
Detailed knowledge of policy	0.192		0.261	0.187		0.261	0.173		0.262	0.179		0.262
Postive opinions on PEVs	0.155	#	0.087	0.150	#	0.087	0.172	#	0.088	0.153	#	0.088
Neighborhood effect				0.053		0.123	0.069		0.123	0.055		0.123
Environmental attitudes							-0.105		0.072			
Innovativeness										-0.011		0.051
SD	0.133		0.669	0.107		0.701	0.102		0.704	0.099		0.707
Battery quality												
ASC	2.092	***	0.068	2.025	***	0.063	2.025	***	0.063	2.026	***	0.063
Knowledge of PEVs	-0.002		0.019	-0.001		0.019	-0.001		0.019	0.010		0.020
Knowledge of policy	0.225		0.142	0.212		0.138	0.205		0.140	0.198		0.139
Detailed knowledge of policy	0.521		0.272	0.492	#	0.267	0.485	#	0.267	0.458	#	0.268
Postive opinions on PEVs	-0.167		0.088	-0.164	#	0.086	-0.155	#	0.088	-0.138		0.087
Neighborhood effect				0.074		0.126	0.081		0.126	0.089		0.126
Environmental attitudes							-0.041		0.072			
Innovativeness										-0.091	#	0.050
SD	0.873	***	0.190	0.490	#	0.260	0.491	#	0.260	0.494	#	0.259
Usage cost												
ASC	0.598	***	0.036	0.594	***	0.036	0.594	***	0.036	0.596	***	0.036
Knowledge of PEVs	0.019		0.016	0.019		0.015	0.019		0.015	0.025		0.016
Knowledge of policy	0.004		0.126	0.006		0.123	-0.002		0.124	-0.005		0.124
Detailed knowledge of policy	0.477	*	0.239	0.472	*	0.233	0.464	*	0.233	0.448	#	0.234
Postive opinions on PEVs	-0.059		0.079	-0.055		0.077	-0.045		0.078	-0.037		0.079
Neighborhood effect				-0.010		0.114	-0.003		0.114	0.002		0.114
Environmental attitudes							-0.048		0.064			
Innovativeness										-0.060		0.045
SD	0.662	***	0.156	0.370	#	0.219	0.369	#	0.219	0.378	#	0.216
AIC	18630.240			18575.710			18585.850			18565.370		
Log Likelihood	-9185.10			-9167.86			-9162.92			-9152.70		
obs.	7986			7986			7986			7986		

Notes: # p<0.10, * P<0.05, ** p<0.01, *** p<0.001. Socio-economic variables are omitted from table.

Table 10 Mixed logit model results for Hangzhou sample

Variables	Model1 Coef.	Model1 S.E.	Model2 Coef.	Model2 S.E.	Model3 Coef.	Model3 S.E.	Model4 Coef.	Model4 S.E.
Reactions								
ASC	-2.304***	0.165	-2.389***	0.434	-2.389***	0.422	-2.386***	0.366
Knowledge of PEVs	-0.187	0.144	-0.179	0.151	-0.179	0.150	-0.162	0.150
Knowledge of policy	-0.134	0.175	-0.101	0.183	-0.096	0.182	-0.131	0.180
Detailed knowledge of policy	0.028	0.254	0.003	0.264	0.047	0.264	0.029	0.262
Neutral opinions on PEVs	-0.205	0.177	-0.188	0.186	-0.187	0.185	-0.125	0.185
Postive opinions on PEVs	-0.103	0.185	-0.098	0.198	-0.058	0.196	0.068	0.202
Neighborhood effect	0.072	0.140	0.076	0.146	0.099	0.147	0.094	0.146
Environmental attitudes			-0.009	0.078				
Innovativeness					-0.171	0.090		
Social followers							-0.297**	0.093
SD	-0.066	2.545	0.475	1.223	0.460	1.223	0.292	1.643
Driving range								
ASC	0.947***	0.073	0.919***	0.082	0.919***	0.083	0.920***	0.082
Knowledge of PEVs	0.215	0.123	0.206	0.125	0.203	0.125	0.213	0.125
Knowledge of policy	-0.012	0.148	-0.018	0.150	-0.019	0.150	-0.033	0.150
Detailed knowledge of policy	0.177	0.211	0.107	0.214	0.096	0.215	0.117	0.213
Neutral opinions on PEVs	-0.424**	0.150	-0.467**	0.155	-0.468**	0.154	-0.435**	0.154
Postive opinions on PEVs	-0.681***	0.157	-0.763***	0.167	-0.772***	0.165	-0.680***	0.167
Neighborhood effect	0.344**	0.115	0.388**	0.119	0.384**	0.119	0.397***	0.119
Environmental attitudes			0.004	0.065				
Innovativeness					0.039	0.070		
Social followers							-0.145*	0.068
SD	0.081	1.670	0.181	1.071	0.180	1.080	0.184	1.054
Charging time								
ASC	-0.064	0.060	-0.108	0.066	-0.103	0.064	-0.103	0.065
Knowledge of PEVs	0.061	0.132	0.018	0.134	0.033	0.134	0.039	0.134
Knowledge of policy	-0.157	0.162	-0.149	0.164	-0.167	0.163	-0.177	0.164
Detailed knowledge of policy	0.019	0.232	0.026	0.235	0.026	0.235	0.013	0.235
Neutral opinions on PEVs	-0.183	0.166	-0.185	0.171	-0.147	0.170	-0.131	0.171
Postive opinions on PEVs	-0.152	0.172	-0.227	0.180	-0.135	0.178	-0.113	0.181
Neighborhood effect	0.041	0.128	0.026	0.130	0.040	0.131	0.031	0.130
Environmental attitudes			0.119	0.070				
Innovativeness					-0.091	0.076		
Social followers							-0.083	0.073
SD	-0.015	1.701	0.106	1.506	0.083	1.583	0.089	1.568
Charging infrastructure								
ASC	0.306***	0.061	0.263***	0.062	0.266***	0.061	0.264***	0.061
Knowledge of PEVs	0.025	0.133	-0.008	0.134	-0.002	0.134	-0.002	0.133
Knowledge of policy	0.261	0.177	0.293	0.179	0.280	0.179	0.284	0.179
Detailed knowledge of policy	0.423	0.246	0.408	0.247	0.425	0.248	0.397	0.247
Neutral opinions on PEVs	-0.215	0.171	-0.276	0.174	-0.254	0.173	-0.260	0.174
Postive opinions on PEVs	-0.168	0.174	-0.279	0.180	-0.192	0.178	-0.250	0.181
Neighborhood effect	0.028	0.127	0.049	0.128	0.076	0.128	0.049	0.128
Environmental attitudes			0.062	0.070				
Innovativeness					-0.178*	0.079		
Social followers							0.008	0.077
SD	0.250	1.222	0.117	1.574	0.131	1.535	0.132	1.539
Reliability								
ASC	2.575***	0.167	2.577***	0.191	2.581***	0.194	2.583***	0.191
Knowledge of PEVs	-0.191	0.130	-0.179	0.133	-0.207	0.133	-0.192	0.133
Knowledge of policy	-0.406*	0.163	-0.437**	0.168	-0.410*	0.168	-0.432*	0.168
Detailed knowledge of policy	-0.417	0.233	-0.457	0.239	-0.370	0.240	-0.411	0.239
Neutral opinions on PEVs	0.017	0.159	0.033	0.167	-0.022	0.165	0.030	0.166
Postive opinions on PEVs	-0.111	0.163	-0.057	0.174	-0.070	0.171	-0.007	0.176
Neighborhood effect	0.065	0.123	0.107	0.126	0.146	0.127	0.117	0.126
Environmental attitudes			-0.184**	0.070				
Innovativeness					-0.303***	0.078		
Social followers							-0.257***	0.074
SD	0.161	0.773	0.260	0.701	0.258	0.709	0.254	0.071

Variables	Model1			Model2			Model3			Model4		
	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.
Air pollution reduction												
ASC	-0.086		0.063	-0.100		0.064	-0.104		0.064	-0.108		0.065
Knowledge of PEVs	-0.437	**	0.137	-0.482	***	0.140	-0.497	***	0.140	-0.510	***	0.140
Knowledge of policy	-0.008		0.157	-0.024		0.160	-0.012		0.160	0.004		0.160
Detailed knowledge of policy	0.295		0.226	0.241		0.228	0.231		0.230	0.250		0.229
Neutral opinions on PEVs	-0.436	**	0.161	-0.427	**	0.165	-0.466	**	0.164	-0.503	**	0.165
Postive opinions on PEVs	-0.204		0.164	-0.233		0.171	-0.338	*	0.169	-0.401	*	0.173
Neighborhood effect	0.137		0.125	0.146		0.127	0.125		0.127	0.137		0.127
Environmental attitudes				-0.106		0.068						
Innovativeness							0.139	#	0.074			
Social followers										0.174	*	0.073
SD	0.205		0.683	0.218		0.663	0.219		0.661	0.217		0.664
CO2 emission reduction												
ASC	-0.325	***	0.066	-0.348	***	0.068	-0.351	***	0.068	-0.349	***	0.068
Knowledge of PEVs	-0.353	**	0.136	-0.353	*	0.137	-0.369	**	0.137	-0.370	**	0.137
Knowledge of policy	0.267		0.164	0.272		0.166	0.300		0.166	0.295		0.166
Detailed knowledge of policy	0.684	**	0.233	0.650	**	0.233	0.655	**	0.234	0.674	**	0.233
Neutral opinions on PEVs	-0.490	**	0.159	-0.461	**	0.163	-0.505	**	0.161	-0.510	**	0.162
Postive opinions on PEVs	-0.518	**	0.165	-0.480	**	0.172	-0.599	***	0.170	-0.577	***	0.174
Neighborhood effect	-0.136		0.126	-0.120		0.127	-0.147		0.127	-0.124		0.127
Environmental attitudes				-0.135	*	0.068						
Innovativeness							0.155	*	0.074			
Social followers										0.047		0.073
SD	0.237		0.587	0.210		0.622	0.215		0.617	0.214		0.613
Incentives												
ASC	-0.317	***	0.062	-0.353	***	0.065	-0.352	***	0.065	-0.352	***	0.065
Knowledge of PEVs	-0.090		0.129	-0.026		0.130	-0.024		0.130	-0.021		0.130
Knowledge of policy	-0.428	**	0.157	-0.421	**	0.160	-0.424	**	0.161	-0.432	**	0.161
Detailed knowledge of policy	-0.050		0.223	-0.050		0.226	-0.045		0.226	-0.048		0.225
Neutral opinions on PEVs	0.004		0.165	-0.012		0.171	-0.008		0.169	0.006		0.171
Positive opinions on PEVs	-0.041		0.170	-0.070		0.180	-0.053		0.177	-0.027		0.181
Neighborhood effect	0.115		0.123	0.122		0.125	0.128		0.125	0.127		0.125
Environmental attitudes				0.011		0.069						
Innovativeness							-0.040		0.074			
Social followers										-0.068		0.072
SD	0.124		0.620	0.181		0.612	0.187		0.606	0.190		0.599
Battery quality												
ASC	1.299	***	0.049	1.231	***	0.052	1.233	***	0.052	1.231	***	0.053
Knowledge of PEVs	0.227		0.137	0.212		0.139	0.213		0.138	0.220		0.139
Knowledge of policy	-0.198		0.171	-0.173		0.173	-0.177		0.173	-0.188		0.173
Detailed knowledge of policy	0.118		0.243	0.130		0.246	0.135		0.247	0.137		0.245
Neutral opinions on PEVs	-0.173		0.171	-0.156		0.179	-0.151		0.178	-0.125		0.179
Postive opinions on PEVs	-0.308		0.175	-0.325		0.186	-0.303		0.184	-0.248		0.188
Neighborhood effect	-0.071		0.131	-0.052		0.134	-0.045		0.134	-0.044		0.134
Environmental attitudes				0.021		0.076						
Innovativeness							-0.042		0.081			
Social followers										-0.114		0.082
SD	-0.004		2.261	-0.021		2.298	-0.020		2.306	-0.026		2.269
Usage cost												
ASC	0.313	***	0.033	0.275	***	0.034	0.277	***	0.034	0.277	***	0.034
Knowledge of PEVs	0.109		0.117	0.104		0.118	0.110		0.118	0.113		0.118
Knowledge of policy	-0.066		0.146	-0.051		0.148	-0.060		0.148	-0.062		0.148
Detailed knowledge of policy	0.117		0.209	0.100		0.211	0.098		0.211	0.097		0.211
Neutral opinions on PEVs	0.029		0.149	-0.013		0.154	0.004		0.153	0.010		0.154
Postive opinions on PEVs	0.075		0.153	0.018		0.160	0.052		0.158	0.060		0.162
Neighborhood effect	-0.083		0.112	-0.083		0.114	-0.079		0.114	-0.081		0.114
Environmental attitudes				0.052		0.063						
Innovativeness							-0.018		0.068			
Social followers										-0.020		0.066
SD	0.217		0.259	0.242		0.250	0.244		0.249	0.239		0.251
AIC	20,997.410			20,482.360			20,457.855			20,456.805		
Log Likelihood	-10,368.705			-10,101.180			-10,088.927			-10,088.402		
obs.	8,976			8,778			8,778			8,778		

Notes: # p<0.10, * P<0.05, ** p<0.01, *** p<0.001. Socio-economic variables are omitted from table.

WTP results

Test statistics show that the parallel regression assumption has been violated when applying ordered logit to both samples, thus MNL were applied to two samples and combined dataset for analyzing the difference across two cities respondents' WTP on PEVs. Table 11 is the MNL result for combined dataset based on choice of non-willing to pay for PEVs. In this model, *city* is the dummy variable of cases' location (=1 if the case is from Hangzhou). Because the latent variables are obtained separately, they were not included in this pooled samples' analysis but added in separate models. Social influence variables, knowledge of policy and PEVs are examined. Socio-demographic variables such as kids under 18, PEV experiences and car owner ship were dropped from the model due to low significance, Knowledge on PEVs and policy, and observability are dropped due to non-significance.

The result is reliable from the outcome that low income respondents tend to choose low bids for PEVs. The probability of WTP for a cheaper PEV is lower in Hangzhou but higher for high-end vehicle adoption, which indicates a relatively higher income level or consumption level in Hangzhou. Social influence, such as positive opinions and neighborhood effects seems associated with greater probability of the WTP, while neighborhood effects have a relatively stronger effect on high-end PEVs. To save space, Table 11 only includes neighborhood effects.

Table 11 Results of MNL model for WTP across Two Cities (based on no WTP)

Variables	<\100,000	\100,000-149,999	\150,000-199,999	\200,000-249,999	\250,000-299,999	\300,000-349,999	>=\350,000
Age	-0.020 *	-0.052 **	-0.055 **	-0.014	-0.020	-0.045	-0.012
	(0.016)	(0.015)	(0.017)	(0.016)	(0.018)	(0.019)	(0.019)
Gender	-0.611 #	-0.155	-0.196	-0.006	-0.173	0.095	0.936 #
	(0.354)	(0.340)	(0.360)	(0.376)	(0.403)	(0.602)	(0.467)
Years of schooling	-0.067	-0.010	-0.024	0.104	0.154 #	-0.053	0.101
	(0.062)	(0.061)	(0.066)	(0.071)	(0.080)	(0.116)	(0.084)
City	-1.479 ***	-0.380	0.473	0.808 #	0.697	1.127	1.742 **
	(0.399)	(0.370)	(0.395)	(0.429)	(0.459)	(0.688)	(0.563)
Household income	-0.706 **	-0.006	-0.006	0.438 #	0.547 *	0.688 #	0.544 #
	(0.241)	(0.228)	(0.242)	(0.254)	(0.272)	(0.397)	(0.288)
Car use frequency	0.079	0.136	0.313 *	0.235 #	0.214	0.707	0.490 *

	(0.132)		(0.125)		(0.139)		(0.142)		(0.155)		(0.362)		(0.194)
Interpersonal communication	0.515	*	0.617	**	0.414		0.731	**	0.785	**	0.340		0.966	**
	(0.247)		(0.236)		(0.249)		(0.263)		(0.282)		(0.389)		(0.301)
Neighborhood effect	0.343		0.534		0.809	*	0.364		0.759	#	2.078	**	0.868	*
	(0.385)		(0.368)		(0.387)		(0.407)		(0.430)		(0.677)		(0.458)
ASC	11.208	***	2.397		1.469		-7.900	*	-10.148	**	-11.668	*	-12.661	**
	(3.057)		(2.925)		(3.133)		(3.326)		(3.62)		(5.440)		(3.913)
Log- Likelihood							-1,266.559						
Nagelkerke's R^2							0.376						
AIC							2,659.594						
BIC							2,951.594						
N							767						

# p<0.10, * P<0.05, ** p<0.01, *** p<0.001. S.E. statistics in parentheses.

Table 12 Results of MNL model (Hangzhou)

Variables	<\100,000	\100,000-149,999	\150,000-199,999	\200,000-249,999	\250,000-299,999	\300,000-349,999	More than \350,000
Age	-0.058 *	-0.061 **	-0.055 *	-0.030	-0.040	-0.061	-0.024
	(0.025)	(0.020)	(0.021)	(0.020)	(0.022)	(0.039)	(0.023)
Years of schooling	-0.188 #	-0.020	-0.019	0.073	0.073	0.130	0.078
	(-0.108)	(0.956)	(0.099)	(0.100)	(0.110)	(0.177)	(0.114)
Household income	0.001	0.691 *	0.200	0.580	0.610	0.321	0.574
	(0.395)	(0.349)	(0.348)	(0.351)	(0.371)	(0.504)	(0.379)
Car use frequency	0.292	0.048	0.252	0.220	0.214	0.880	0.482 *
	(0.204)	(0.165)	(0.173)	(0.173)	(0.190)	(0.474)	(0.228)
Neighborhood effect	0.076	0.685	1.325 *	0.843	1.121	2.646 **	1.025
	(0.725)	(0.630)	(0.630)	(0.636)	(0.661)	(0.931)	(0.679)
Positive opinion	1.394 **	0.223	-0.037	0.396	0.497	0.021	0.623

	(0.472)	(0.384)	(0.387)	(0.391)	(0.415)	(0.545)	(0.430)
Environmental attitudes	0.027 #	0.491 #	0.612 *	0.494	0.500	-0.585	0.407
	(0.351)	(0.295)	(0.299)	(0.301)	(0.320)	(0.441)	(0.330)
Innovativeness	0.722 #	1.177 **	0.729 *	0.884 *	1.121 **	0.250	1.580 ***
	(0.386)	(0.341)	(0.343)	(0.344)	(0.364)	(0.485)	(0.380)
ASC	2.889	-4.680	0.318	-6.852	-7.473	-8.616	-9.023
	(5.465)	(4.735)	(4.787)	(4.826)	(5.144)	(7.500)	(5.338)
Log-Likelihood				-706.520			
Nagelkerke's R^2				0.313			
AIC				1,539.049			
BIC				1,790.661			
N				401			

# p<0.10, * P<0.05, ** p<0.01, *** p<0.001. S.E. statistics in parentheses.

Table 13 Results of MNL model (Linyi)

Variables	< \100,000	\100,000-149,999	\150,000-199,999	\200,000-249,999	\250,000-299,999	\300,000-349,999	More than \350,000
Age	0.034	0.003	-0.013	0.075 #	0.072	-0.019	0.034
	(0.920)	(0.080)	(-0.300)	(1.710)	(1.430)	(-0.150)	(0.410)
Years of schooling	-0.032	-0.004	-0.067	0.088	0.250 #	-0.757 #	0.423
	(-0.320)	(-0.030)	(-0.600)	(0.670)	(1.720)	(-1.700)	(1.270)
Household income	-1.394 ***	-0.745 *	-0.130	0.483	0.806 #	3.122 #	2.225 *
	(-3.850)	(-2.140)	(-0.350)	(1.130)	(1.690)	(1.930)	(2.200)
Neighborhood effect	0.184	0.340	0.240	-0.485	-0.054	3.812	3.160 #
	(0.340)	(0.630)	(0.410)	(-0.690)	(-0.070)	(1.440)	(1.690)
Positive opinion	1.240	1.559 *	1.503 #	1.629 #	1.990 *	-1.532	2.355 #
	(1.560)	(1.980)	(1.820)	(1.800)	(2.070)	(-0.600)	(1.690)
Environmental attitudes	0.386	0.388	0.529	0.246	-0.292	0.899	-1.143
	(1.150)	(1.160)	(1.430)	(0.570)	(-0.620)	(0.660)	(-1.190)

Innovativeness	-0.520	-0.097	0.044	0.334	0.284	2.548	3.331 *
	(-1.350)	(-0.250)	(0.110)	(0.700)	(0.530)	(1.170)	(2.300)
ASC	17.169 ***	10.060 *	3.350	-9.872 #	-16.870 *	-35.246 #	-42.164 *
	(3.720)	(2.230)	(0.690)	(-1.690)	(-2.510)	(-1.890)	(-2.530)
Log- Likelihood				-549.414			
Nagelkerke's R2				0.419			
AIC				1031.738			
BIC				1247.782			
N				350			

Notes: # p<0.10, * P<0.05, ** p<0.01, *** p<0.001. t statistics in parenthese.

According to the result of Hangzhou model (Table 12), respondents who receive positive opinions on PEVs are more likely to pay a lower price, while neighborhood effects tend to be more effective with a relatively higher priced vehicle uptake intention. In regard to psychological factors, respondents with higher innovative scores are more willing to adopt PEVs under larger range of bids, while respondents with high environmental attitudes are more willing to pay PEV at relatively lower price (the average level).

The result of Linyi model (Table 13) shows a different picture. Household income strongly affects respondents' choice. Positive opinion has a bigger effect on WTP at the range from ¥100,000 to ¥300,000. The latent variable environmental attitudes has no impact while innovativeness become significant when the bid is highest(More than ¥350,000). The alternative specific constants (ASCs) are highly significant which indicates respondents are quite sensitive to the prices.

Robustness Checks

The first robustness check is running the ordinal regression analysis of pooled samples for WTP to check how heterogeneity across participants affects the aggregate result (Appendix).

7. Discussion

This study compared the contribution of knowledge, social influence and attitudes as well as social norms on consumer preference in city with and without restrictions.

Reliability, as the most important features selected by most respondents, is negatively associated with knowledge of policy, and positively related with social influence (positive opinion) based on purchasing costs.

Knowledge of policy improves consumers' confidence on reliability and the preference on CO_2 emission function compare to purchasing costs in Hangzhou sample, but increases the preference on charging infrastructure and driving range in Linyi sample. This indicates the penetration of policy incentives is different in cities with and without restrictions. In Linyi, without number plate restriction and driving restrictions, consumers are less motivated to learn policy incentives/subsidies for

PEVs. In contrast, consumers with limited chance to win a license lottery in cities like Hangzhou have to consider PEVs which motivates them to collect information on subsidies and then probably find the models that listed in government category are trustable. As Zhuge and Shao (2019) stated, those restrictions played quite important roles.

If we further look at the degree of understanding the policy/subsidies, various impacts are observed in two samples. Knowledge about policy/subsidies has been tested using two dummy variables, know the policy/subsidies, and know detailed information about policy. Respondents who know detailed information about policy/subsidies do not significantly worry about charging infrastructure (Linyi sample), but pay more attention on driving range (Linyi sample) or CO_2 emission reduction (Hangzhou sample). This result indicates those who know the policy well known where subsidies goes for. While respondents who did not know the detailed information about policy tend to think charging infrastructure as a barrier (Linyi sample) or think incentives are not important (Hangzhou sample). This is probably because people are less informed/neglect about the existing charging net in their city.

Knowledge plays less important role than social influence in terms of WTP for PEVs, which is consistent with the founding by Ma et al. (2019). However, with detailed information about policy/subsidies, people are more confident about PEVs uptake generally. How to drive consumers to search for information and enlarge their knowledge is the first step in PEV uptake intention formation.

Social influence on attributes preferences in two cities(H2-1) as well as WTP(H2-2 and H2-3) are confirmed. The first finding is, interpersonal communication is more influential compare to neighborhood effects on consumers' preferences. It lowers the preference on environmental contributions features in both cities compare to purchasing costs. During the face-to-face interviews, some respondents expressed their worries of the source of electricity used by PEVs, whether the electricity is generated from coal or natural gas, but others are more cost concerned. Thus, the information they collected from their social networks is probably more focuses on costs rather than environmental contribution of PEVs.

The second finding is, social influence works slightly differently across cities with and without restrictions. Tests have revealed that the difference of social influence across two samples is not significant. Thus, these differences may due to the characteristics of cities. People who received positive comments on PEVs tend to rank charging infrastructure and reliability more important, but neighborhood effects are not significant in Linyi. Combined the similar results from knowledge of policy, people in Linyi may less confident with infrastructure generally. In contrast, the results in Hangzhou shows interpersonal communication lower the preference on the driving range, while neighborhood effects positively affects the preference of it. This result indicates without interpersonal discussion, observing PEV use, probably observing less convenience PEVs charging, might incur worries about the driving range in Hangzhou.

In terms of the effects on WTP, social influence variables distinct with each other as a results of market differences. When the bid for PEV is less than ¥100,000, compare to respondents who has no plan to buy a PEV, interpersonal communication is positively significant in Hangzhou especially for cheap PEVs but not in Linyi. During the interview in Linyi, there are large number of cheap Electric bikes which can accommodate three people or micro BEVs running in the city as small taxies. Residents have a bad imagine of them which may affect their choice in WTP question. In contrast, Hangzhou forbid using this type of transportations, but domestic, low-end micro BEVs receive neutral assessments. It seems there are various opinion on different types of PEVs thus the opinions are inconsistent across different regions or markets.

Aforementioned in the review part, there is very limited number of paper included social influence as a influential factor in domestic studies. Pettifog et al.(2017) found the effect size of social influence is around 0.086 to 0.343 and the effect of social influence in China is low. Habich-Sobiegalla et al. (2018) found that the effect size of neighborhood effects in China is 0.628, which is lower than Russian (0.945) and Brazil (0.697). This study provides new evidences on this issue. Neighborhood effects tends to be more influential than interpersonal communication when the bid is low or very high. The coefficients are relatively higher when the bids go up. The different results may due to different models using. However, in the ordered logistic model (Appendix), the coefficients are 0.324 (positive opinion) and 0.370

(neighborhood effects), which fell into the CIs of effect size for each type based on Pettifor et al.(2017). The WTP results also indicate that residents in Hangzhou may discuss less on the goods they own but more easily be affected by what they saw, while residents in Linyi may involve in a larger community where they are more likely to be influence by the assessment of others.

Attitudes/social norms

The influence of environmental attitudes on preferences almost cannot be observed in Linyi sample. A surprising result is environmental attitudes negatively associated with CO_2 emission reduction feature in both samples. It is probably because the models are based on purchasing costs. In contrast, it lowers the likelihood of ranking reliability as an most important feature in Hangzhou sample. This result is somehow consistent with the findings by Wang et al. (2017), who stated that environmental concern have limited contribution in PEV uptake. Environmental attitudes might be a weak factor in promoting PEV uptake in China. During the survey, people discuss about the source of electricity. 85.72% of the electricity in Shangdong Province is generated from thermal power. In contrast to Shandong province, the percentage is approximately 60% in Zhejiang Province (China Energy Statistics Yearbook 2018).

PEV support policy has successfully improved the confidence of using PEVs(reliability) but rare information about the deployment of grid storage/power source is advertised.

The impacts from innovativeness are much greater than environmental attitudes. It negatively contributes to the preferences on charging infrastructure (two samples), charging time, battery quality (Linyi sample), and reliability (Hangzhou sample). It positively associated with preferences on air pollution and CO_2 emission reduction in Hangzhou sample. For the first time, we found that innovativeness could contribute to PEV uptake in cities in China. It reveals different dimensions of residents' attitudes in two cities. People in Hangzhou are more environmental oriented innovators while residents in Linyi are more technological oriented innovators.

The various influences of attitudes can also be found in WTP models. The positive effects of environmental attitudes on WTP in Hangzhou model support the hypothesis. However, the impacts of environmental attitudes are weak again in Linyi sample. People with higher innovative value in Hangzhou tend to purchase PEVs at the average prices, while the results in Linyi shows innovativeness positively correlated with high-end PEVs only. This result again indicates people with innovative attitudes are more interested in the technology development in Linyi.

The additional social follower variable contributes to lower the likelihood on choosing driving range, reliability in Hangzhou sample. People with higher social follower scores tend to pay more attention on air pollution reduction rather than CO2 emission reduction. However, there is no evidence show it significantly correlated with purchase intention.

Results of socio-demographic characteristics show household income and car use frequency are two most important factors in terms of PEV uptake, which is consistent with previous studies (Qian and Soopramanien, 2011). Household income is highly and positively related to the preference of charing time, which indicates the value of time is been weighted importantly with the increasing of income. Car use frequency also plays important role in PEV uptake. It correlates with WTP and preferences of CO_2 emission reduction in Hangzhou but not in Linyi. This is a variable which reflects the life style of a family or business-related activity. Car use frequency is independent with household income level in both cities, thus, it is probably the business style or the different industry structures in two cities can explain the different impacts from car use frequency on residents. Moreover, there is no evidence to support PEV experience (being in a PEV taxi, bus or driving experience) can affect both purchasing decision and attributes preference in China, which is consistent with the results found by Habich-Sobiegalla et al. (2018).

8. Conclusions

This study contributes to the literature on PEV uptake by systematically examining a group of psychological factors on consumer preferences within China from not just first or second-tier cities but compare two cities with and without restrictions. It furthers our understanding whether social influence, attitudes /social norms, and knowledge affects differently across regions. Various influence from these factors across cities with and without restriction are observed. Knowledge and environmental attitudes are weak factors compare to innovativeness and social influence. The different impacts from social influence and innovativeness are oriented from the features of domestic markets, to be specific, the introduction of number plate restrictions, the level of urbanization, and local industry as well.

Based on the findings, this study has generated practical implications for policy designers and car makers. Restriction policies such as license lottery policy affect the PEV uptake intention but basically on the cheapest or highest PEVs, the purchasing intension across large range of prices can be affected through various channels. A simultaneous plan for building a clean power network might facilitate PEVs among environmentalists.

For local authorities in Hangzhou, a more convenient charging system should be designed or promoted to lower present negative neighborhood effects. For car makers, since reliability and battery quality are ranked as the most important attributes, and the probability of choosing reliability is positively correlated with social influence variables in Linyi sample, to improve the reputation of PEVs might be a critical issue there. Emphasizing the technology development of charging time, or shorten the charging time, may largely increase the probability of PEV uptake among higher income groups.

However, the influence of psychological factors may change with the development of PEVs, dynamic studies are needed to follow up the progress. In addition, Hangzhou and Linyi are both locates along the East coast, thus the results of this study cannot be generalized to other regions in China.

Acknowledgment