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From government to market? A discrete choice analysis of policy instruments for
electric vehicle adoption

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Abstract: With the calls for policy instruments to shift from “government” to “market”, surging interest leads to a broad debate on the role of market-oriented policy instruments in promoting the adoption of electric vehicles (EVs). As the two prime examples of market-oriented policy instruments, personal carbon trading (PCT) and tradable driving credit (TDC) schemes are theoretically regarded to alter consumers’ EV preferences by both economic and psychological motivations. However, limited studies validate such effects. To fill the gaps, we conduct a discrete choice experimental survey by integrating vehicle, psychological, and policy attributes together. The empirical results from China reveal how consumers make trade-offs between economic and psychological motivations. In particular, although PCT and TDC can stimulate consumers’ EV adoption behaviors through monetary revenues, the positive effect of more revenues from PCT and TDC in promoting EV adoption is not always supported because EV adoption is subject to some psychological attributes, especially perceived norm pressures. It implies that consumers with stricter norms will be driven more by social and moral pressures than by monetary revenues. Even so, PCT and TDC are considered to be more powerful and sustainable than existing financial incentives. These findings not only contribute to the understanding of the interaction between psychological and policy attributes, but also provide insights for policymakers to design novel policy instruments to promote EV adoption.

Keywords: Electric vehicles; Psychological attributes; Policy attributes; Personal carbon trading; Tradable driving credits; Choice experiment

1. Introduction

As one of the most important environmental innovation products, electric vehicles (EVs) are highly anticipated owing to their ability to maintain energy security and mitigate emissions (Borghesi, 2015; Penna and Geels, 2015; Del Rio Gonzalez, 2009). However, due to consumer concerns about some product attributes, such as purchase price, cruising range, and battery safety, the diffusion of EVs is relatively slow at the current stage (Jin, 2019). To promote EV adoption, the governments in many countries, such as China, the U.S., and the U.K., have launched several policy instruments, including financial incentives related to vehicle purchase and use, such as purchase subsidies, tax exemptions, and preferential charging, as well as non-financial incentives, such as charging infrastructure improvement and high occupancy vehicle (HOV) lanes access (Zhang et al., 2017; Costantini et al., 2015).

Although financial incentives are considered to be more effective than non-financial incentives in motivating consumers to purchase EVs (Zhang et al., 2018b; Liao et al., 2017), there are two major issues for financial incentives. First, the long-term implementation of financial incentives will lead to massive financial expenditures for governments (Wang et al., 2017a). Second, financial incentives may incur some fraud behaviors (CATARC et al., 2018). At present, a common trend in different countries is to reduce or cancel financial incentives. For example, Denmark and the U.S. state of Georgia have canceled tax exemptions, and China plans to eliminate purchase subsidies after 2020 (CATARC et al., 2018). However, EV sales fell dramatically after the authorities repealed their tax exemptions in Denmark and the U.S. state of Georgia (CATARC et al., 2018; Badertscher, 2015). To overcome such a dilemma, there is an urgent need for governments to design novel policy instruments as alternatives to existing

financial incentives.

Different from existing financial incentives that require governments' funding, in recent years, there has been an increasing interest in discussing policy instruments regulated by market mechanisms, namely market-oriented policy instruments (Li et al., 2019a). Compared with existing financial incentives (e.g., purchase subsidies and tax exemptions), the government plays the role of a regulator rather than a monetary provider in the market-oriented policy instruments, which can greatly reduce the government's financial expenditures and subsidy-related fraud behaviors (Xu and Su, 2016). As the two prime examples of market-oriented policy instruments, personal carbon trading (PCT) scheme is proposed from the perspective of carbon mitigation, which requires the government first to establish a trading market with carbon credits as the main commodity, and then set some trading rules (e.g., clarifying the initial credit line and punitive measures) to ensure that each individual can offset their own energy consumption during each compliance period (Starkey, 2012). Because the number of carbon credits consumed by different individuals in each compliance period varies, it will lead to changes in the interests of individuals. On one hand, individuals who consume fewer carbon credits than the initial credit line will profit by selling the remaining credits; on the other hand, individuals who consume more carbon credits than the initial credit line will need to pay for their extra credits (Li et al., 2018a). Similar to the operating mechanism of PCT, tradable driving credits (TDC) scheme also needs the government to build a trading market and to set the initial credit line, but with a fundamental difference, in that TDC is based on the perspective of relieving road congestion and adopting driving credits as the main commodity. It means that TDC requires drivers to decide whether to sell or buy driving credits to realize the trade-offs

between financial benefits and the basic commuting needs (Zhao et al., 2018).

As mentioned before, when the consumed credits are fewer than the initial credit line, both PCT and TDC can provide individuals with certain economic benefits to increase their willingness to adopt EVs. Such an effect is similar to existing financial incentives (e.g. purchase subsidies and tax exemptions) because they alter individuals’ behaviors through economic motivations (Li et al., 2019b). However, recent studies have revealed that since PCT emphasizes the importance of carbon mitigation, PCT can awaken individuals’ psychological motivations (e.g., normative and pro-environmental motivations), thereby promoting low-carbon behaviors (Li et al., 2019b; Raux et al., 2015). Similarly, Dogterom et al. (2018) have found that TDC can affect an individual’s travel intentions through psychological factors, because TDC can enhance individuals’ convenience motivations via improving transportation system efficiency (Wang et al., 2019; Xu et al., 2017; Bao et al., 2014). To sum up, PCT and TDC can theoretically stimulate individuals’ extra psychological motivations in addition to economic motivations (see Fig. 1). However, to our knowledge, although some studies have analyzed the role of PCT in promoting EV adoption (Li et al., 2019b; Li et al., 2018b), there is still a lack of empirical evidence on how consumers make trade-offs between different market-oriented policy instruments and how market-oriented policy instruments alter consumer’s EV adoption behavior by influencing psychological factors.

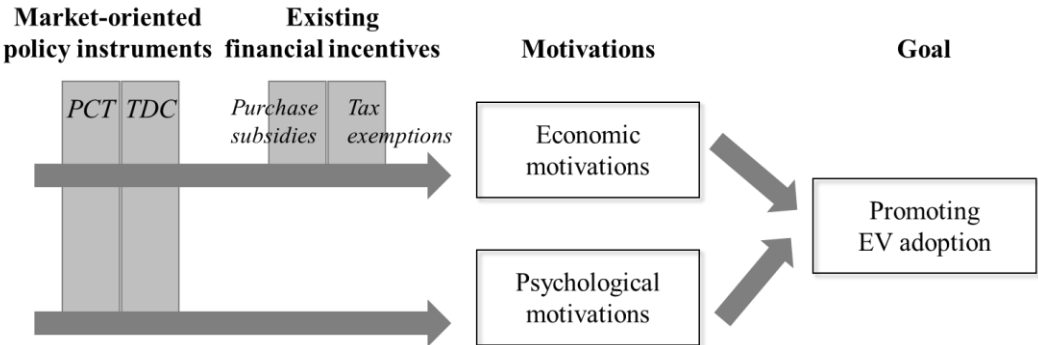


Fig. 1. The routes of different policy instruments

To this end, we conducted a discrete choice experimental survey in China by integrating vehicle attributes, psychological attributes, and policy attributes together. We set up two choice scenarios to compare consumer preferences among the different types of existing policy instruments, PCT and TDC, and to explore whether more revenues from PCT and TDC can always encourage consumers to adopt EVs. After analyzing 1546 respondents who are private car owners or the population intending to buy a new car within three years, we illustrated consumer preferences for PCT and TDC and how psychological factors influence consumer's EV adoption behavior, as well as the change in consumer attitudes towards vehicle attributes. Our study contributes to the literature in the following two aspects.

First, we incorporate psychological attributes with vehicle choice experiments, thereby responding to calls by Liao et al. (2017) for empirical studies that investigate the combined effects of different attributes in promoting EV adoption. Specifically, on one hand, past studies associated with EV adoption psychology usually adopt structural equation model and regression model to analyze the role of different psychological constructs in promoting EV adoption (Adnan et al., 2018; Du et al., 2018), so they may ignore the influence of vehicle attributes and policy attributes on EV adoption. On the other hand, current vehicle choice experiment research focuses on the trade-offs between vehicle attributes and policy attributes (Wang et al., 2017a), and thus may overlook the interaction between psychological attributes and policy attributes. Different from past work, our study comprehensively integrates vehicle attributes, psychological attributes, and policy attributes together, and analyze the effects of each attribute under different levels, which provides new insights for understanding EV adoption behavior.

Second, from the perspective of policy research, most present vehicle choice experiment studies focus on the impact of existing financial incentives and non-financial incentives on EV adoption (Huang and Qian, 2018; Hackbarth and Madlener, 2013), thus may ignore the potential of some theoretically effective market-oriented policy instruments, such as PCT and TDC. Although Li et al. (2018b) and Li et al. (2019b) have found the role of PCT in promoting EV adoption based on provincial and urban level data, respectively, they do not consider how consumers make trade-offs between different market-oriented policy instruments and how psychological factors play the role in promoting EV adoption. Through a national survey, we not only further confirm that PCT can stimulate consumers' both economic and psychological motivations, but also highlight the role of TDC in promoting EV adoption for the first time. Overall, our findings have a direct impact on the Chinese government to design novel and market-oriented policy instruments to promote EV adoption, and simultaneously can also provide a reference for other countries that face the dilemma of financial incentives in promoting EV adoption, such as the U.S. and Denmark.

The rest of this paper is organized as follows: first, in Section 2, we review the literature. Then, in Section 3, we describe the survey design, while the data collection is introduced in Section 4. The model specification and empirical results are presented in Section 5 and discussed in Section 6. Our conclusions are summarized in Section 7.

2. Literature review

This study mainly relates to two distinct streams of literature: (i) the theoretical factors that influence the adoption of EVs, namely, vehicle attributes, psychological attributes, and

policy attributes, and (ii) the choice experiment approach that simulates the market environment to measure consumer preferences.

2.1 Vehicle attributes related to EV adoption

Vehicle attributes include two aspects: (i) economic attributes, which refer to the monetary costs related to purchase and use; (ii) technical attributes, which refer to the technical characteristics of the vehicle itself (Liao et al., 2017). For economic attributes, the purchase price and operation cost, albeit in different forms, such as the cost per 100 km (Hoen and Koetse, 2014), the annual running cost (Qian et al., 2019), and the fuel cost per month (Byun et al., 2018), are found to have a negative and highly significant influence on EV adoption (Wang et al., 2017a). Preferences for such attributes may vary among populations. Normally, people with higher incomes are less price- and cost-sensitive (Liao et al., 2017), but there are some special cases. For example, Chinese respondents with higher incomes still place higher importance on fuel costs (Helveston et al., 2015). Regarding technical attributes, most studies in different countries have examined the influence of cruising range (Pelletier et al., 2016), charging time (Li et al., 2018b), and battery warranty (Liao et al., 2017) on EV adoption. Preferences for such attributes may be affected by the density of the charging station and the average range of conventional fuel vehicles (CFVs) (Liao et al., 2017).

2.2 Psychological attributes related to EV adoption

As EVs can substantially reduce carbon emissions associated with personal car driving, the adoption of EVs is also related to some psychological attributes. Based on the theory of

planned behavior (TPB) and the norm-activation model (Ajzen, 1991; Schwartz and Howard, 1981), attitude, perceived behavioral control, subjective norms (SN), and personal norms (PN) are the four major predictors for EV adoption behavior. Specifically, attitude refers to the extent to which an individual has a favorable or unfavorable assessment on EVs; perceived behavioral control refers to the perceived ease or difficulty of adopting EVs; SN is perceived social pressure to adopt EVs, while PN is personal or moral feelings of adopting EVs (Adnan et al., 2018). Previous studies have found that these four psychological attributes have a positive and highly significant influence on EV adoption (Huang and Ge, 2019; Mohamed et al., 2018).

Regarding broader pro-environmental theories (Steg and Vlek, 2009), some constructs, such as low-carbon awareness, knowledge, *perceived environmental benefits* (PEB), and environmental concern, have been proposed to investigate the impacts on EV adoption. Specifically, low-carbon awareness refers to an individual's opinions on low-carbon behavior, and knowledge refers to a kind of ability to identify pro-environmental behavior (Du et al., 2018); PEB measures the environmental benefits of using EVs (Zhang et al., 2018a); environmental concern or *environmental awareness* (EA) refers to an individual's opinions towards the environment (Adnan et al., 2018). In the context of China, Du et al. (2018) found that low-carbon awareness and knowledge had marginal moderating effects between EV adoption intention and TPB-related psychological attributes, while Zhang et al. (2018a) found that PEB could affect Chinese consumer's EV adoption behavior by forming a positive attitude towards EVs. Similar to the path of PEB, Adnan et al. (2018) pointed out that environmental concern was an important antecedent for Malaysian consumers to form an attitude towards EVs. Although the above work helps to understand consumers' EV adoption behavior from the

perspective of environmental psychology, it may ignore consumers' trade-offs among different types of attributes, such as psychological attributes and policy attributes, which provides us an opportunity for in-depth analysis.

2.3 Policy attributes related to EV adoption

Policy attributes refer to the various types of policy instruments related to EVs (Liao et al., 2017). Currently, many countries and regions have implemented some policy instruments, including financial incentives and non-financial incentives, to accelerate the diffusion of EVs (Wee et al., 2018; Costantini et al., 2015). However, the importance of the above incentives varies when considering consumer preferences. For example, the number of charging stations was the most important policy factor affecting Norwegian consumers to adopt EVs (Mersky et al., 2016), while Li et al. (2018b) and Jin et al. (2014) pointed out that direct purchase subsidies were the biggest determinant for Chinese and American consumers to purchase EVs. Although financial incentives have pronounced effects in promoting EV adoption (Wee et al., 2018), from a long term perspective, massive financial expenditures from financial incentives will lead to a common trend that different countries and regions, such as China, Denmark and the U.S. state of Georgia, intend to reduce or cancel financial incentives (CATARC et al., 2018).

To this end, some market-oriented policy instruments, such as PCT and TDC, have been proposed as alternatives to financial incentives (Li et al., 2019b; Li et al., 2018b). In fact, scholars in different countries have confirmed the role of PCT and TDC in changing travel behavior (Parag and Strickland, 2011) or travel intentions (Dogterom et al., 2018). The real case from China also confirms that market-oriented instruments can reduce the driving frequency of

CFV owners (CCTN, 2019). However, in the context of EV adoption, only Fan et al. (2016), Li et al. (2018b), and Li et al. (2019b) studied the effects of PCT on EV adoption. Specifically, Fan et al. (2016) used a mathematical model and found that PCT would have a positive effect on consumer preferences for EVs when the carbon credit price exceeded a critical value. Li et al. (2018b) adopted the choice experiment approach in Jiangsu Province, China and found that PCT was less effective than purchase subsidies, but shown to be more effective than tax exemptions and free parking. On this basis, Li et al. (2019b) further compared consumer preferences for PCT and carbon tax through a survey in Nanjing city, China. To our knowledge, there is no empirical evidence exploring the role of TDC in promoting EV adoption. In addition, although Li et al. (2018b) and Li et al. (2019b) pointed out the role of PCT in promoting EV adoption, they did not analyze whether more PCT revenue would always matter and the interaction with psychological attributes. All these facts encourage us to conduct a detailed analysis to examine the role of PCT and TDC in promoting EV adoption.

2.4 Interaction effects between psychological attributes and policy attributes

Recall that PCT and TDC can theoretically stimulate individuals' extra psychological motivations in addition to economic motivations (Li et al., 2019b). In fact, drawing on the experience in the field of pro-environmental behavior (Steg and Vlek, 2009), the interaction between psychological attributes and policy attributes in the context of EV adoption can be derived as follows. First of all, the relationship between policy attributes and EV adoption behavior may be moderated by psychological attributes such as attitudes, perceived behavioral control, SN, and PN. For example, policy advocacy on the environmental benefits of using EVs

may result in more positive SN and PN, which may, in turn, result in higher EV adoption (Adnan et al., 2018). Secondly, because the effects of policy attributes on behavior may depend on personal factors, policy attributes may moderate the relationship between psychological attributes and EV adoption behavior. For example, the revenues from PCT and TDC or other financial incentives can narrow the price and cost gaps between EVs and CFVs, allowing individuals to have enough perceived behavioral control to afford an EV. Hence, such instruments may work for individuals with higher price sensitivity (Wang et al., 2018). In short, previous studies in different countries usually discuss the impact of psychological attributes and policy attributes on EV adoption separately, which may overlook the potential interplay. Therefore, there is an urgent need to integrate different attributes to enhance the understanding of the role of policy instruments in promoting EV adoption.

2.5 Application of choice experiment in the context of EV adoption

Over the past two decades, stated preference (SP) or experimental choice analysis have been widely used to measure consumer behavior and preferences (Hensher et al., 2015; Kroes and Sheldon, 1988). As an approach that presents different choice tasks for respondents in a hypothetical context, SP or experimental choice analysis can be applied in several fields, such as organic food choice (Janssen and Hamm, 2012), renewable heat obligation choice (Lim et al., 2015), hotel booking channel choice (Xie et al., 2015), and travel mode choice (Yang et al., 2018). In the context of EV adoption, all previous studies related to consumer preferences are based on SP data due to the lack of large-scale market data of EVs (Liao et al., 2017). As for data analysis, all mainstream choice models, such as multinomial logit (MNL) model, nested

logit (NL) model, random parameter logit (RPL) model or mixed logit (MXL) model, and latent class (LC) model, have been included in previous literature (Huang and Qian, 2018; Li et al., 2018b; Wang et al. 2017a; Horne et al., 2005).

Current research on the application of the choice experiment in the context of EV adoption can be divided into two aspects. First, some studies focused on consumer preferences for different vehicle attributes and conducted the corresponding choice experimental survey in South Korea (Byun et al., 2018), Denmark (Jensen et al., 2013), and Canada (Horne et al., 2005). Second, in the context of China (Wang et al., 2017a), the U.S. (Helveston et al., 2015), and Germany (Hackbarth and Madlener, 2013), some research combined vehicle attributes with policy attributes to study the effectiveness of different policy instruments in promoting EV adoption. Although previous literature is helpful to understand consumers' EV preferences, our present study expands on and varies from past studies by investigating consumer preferences for two emerging market-oriented policy instruments, as well as highlighting the interaction between psychological and policy attributes.

3. Choice experimental survey design

Our choice experimental survey consists of four parts. In part one, respondents are first asked to understand the basic concepts related to PCT and TDC (see *Appendix A*), and then they need to complete a quiz to show that they really understand these two market-oriented policy instruments. In part two, respondents need to read two different choice scenarios to understand the policy settings in the future. After reading each choice scenario, respondents are asked to finish two choice tasks to show their preferences for different vehicles, where each choice task

contains one BEV option, one CFV option, and one non-chosen option (i.e., neither). In part three, a 12-item seven-point Likert scale is set to measure respondents' psychological attribute levels. In part four, some questions related to sociodemographic characteristics are set. In this section, we will focus on how to design a choice experiment.

3.1 Reasons for selecting the Chinese auto market as our research objective

As the largest EV market in the world (CATARC et al., 2018), the Chinese EV market is facing a similar dilemma as the EV markets in other countries including the U.S., Denmark, the U.K., and Germany. In particular, the diffusion of EVs largely depends on the government subsidies, whereas the government subsidies are reduced year by year because of massive financial expenditures, which may be at the expense of a sharp drop in sales of EVs (CATARC et al., 2018). Despite this, China is carrying out some PCT-related pilot projects that are ahead of other countries. Specifically, by following the Chinese Certified Emission Reduction (CCER) scheme, CFV owners in Beijing can obtain carbon credits by reducing the driving frequency, and then they can sell these carbon credits on third-party trading platforms for economic benefits (CCTN, 2019; Li et al., 2019a). Therefore, selecting the Chinese auto market as an illustrated case of market-oriented policy instruments is representative, and a detailed study on the policy instruments for the Chinese auto market can not only solve the dilemma of EV development in China theoretically, but also provide an important reference for the diffusion and adoption of EVs in other countries facing similar issues, such as the U.S. and Denmark.

3.2 Vehicle attributes

Because battery electric vehicles (BEVs) accounted for more than 81% of total EV sales in China in 2017 (CATARC et al., 2018), we focus on the major vehicle attributes when consumers make decisions between BEVs and CFVs. Typically, the main factors that affect consumers' BEV adoption behavior include the selling price (Qian et al., 2019), the cost (Cecere et al., 2018), the cruising range (Hess et al., 2012), the (quick) charging time (Li et al., 2018b), the battery warranty (Kwon et al., 2018), the emission standard (Hackbarth and Madlener, 2013), and the density of charging stations (Byun et al., 2018). Since home-use charging piles offered by BEV manufacturers and charging stations constructed by the Chinese government provide convenience for charging BEVs (CATARC et al., 2018), we do not consider the impact of normal charging time and charging station density on EV adoption.

Moreover, as compact cars are the mainstream vehicles in the Chinese automobile market (CATARC et al., 2018), we have selected some representative models of BEVs and CFVs (see Table 1 and Table 2) and determined the level of attributes according to these models. In particular, since the current average selling price of CFVs is approximately 144,600 RMB¹, and the lowest price of CFVs shown in Table 2 is 119,800 RMB, we set the lowest selling price of CFVs to be 120,000 RMB, and the corresponding highest selling price of CFVs can be estimated as 170,000 RMB ($144,600 \text{ RMB} * 2 - 120,000 \text{ RMB}$). For the same series of vehicles produced by the same auto manufacturer, the electric version is usually 80,000 RMB to 130,000 RMB more expensive than the fuel version (Yiche, 2018). If we assume CFVs at a price of 120,000 RMB as the benchmark, then the lowest selling price of BEVs is 200,000 RMB and the highest selling price of BEVs is 250,000 RMB.

¹ <http://tj.eastday.com/eastday/finance/cys/node1202/userobject1ai562511.html>.

Table 1 Some BEV configurations in the Chinese auto market

BEVs	Selling price (10,000 RMB)	Power consumption (kWh/100 km)	Quick charging time (80%, h)	Normal charging time (h)	Cruising range (km)	Battery warranty
Changan EV300	19.23	15	0.75	8	300	5 years or 100,000 km
Roewe Ei5	21.38	11.6	0.75	5.5	300	None
Geely EV450	21.83	13	0.5	9	400	8 years or 150,000 km
BYD Song EV500	27.99	15.5	1.2		500	8 years or 150,000 km

Note: The selling price refers to the unsubsidized price, namely, the manufacturer's suggested price.

Source: Author, summarized via Yiche.com.

Table 2 Some CFV configurations in the Chinese auto market

CFVs	Selling price (10,000 RMB)	Gasoline consumption (L/100 km)	Cruising range (km)	Emission Standard
LA FESTA	11.98	5.4	981	GB VI
Joyear S50	13.29	7.7	1000	GB V
Volkswagen Sagitar	15.38	5.5	1000	GB V
Nissan X-Trail	18.88	6.2	1048	GB VI

Note: The selling price refers to the unsubsidized price, namely, the manufacturer's suggested price.

Source: Author, summarized via Yiche.com.

The cost attribute levels for BEVs and CFVs are indirectly derived from power and gasoline consumption shown in Table 1 and Table 2. As the average power consumption of BEVs is 13 kWh per 100 km (CATARC et al., 2018), we assume that the power consumptions per 100 km of BEVs are 11 kWh and 15 kWh, which are slightly lower than those reported in Table 1. The reason is that BEVs are usually equipped with a kinetic energy recovery system, implying that the actual power consumption per 100 km is usually lower than the design value. In contrast, the actual gasoline consumption per 100 km is usually higher than the design value; thus, we assume that the gasoline consumptions per 100 km of CFVs are 6.5 L and 7.5 L to ensure that the average gasoline consumption is close to the actual average value, 6.9 L (Li et

al., 2018b). Moreover, the charging price of 1 kWh is between 0.8 RMB (normal charging) and 1.5 RMB (quick charging), while the charging efficiency is 0.88 for normal charging and 0.93 for quick charging (CATARC et al., 2018). Hence, the 100-kilometer power cost for BEVs is set as 10 RMB ($0.8 \text{ RMB/kWh} \times 11 \text{ kWh}/0.88$) and 25 RMB ($1.5 \text{ RMB/kWh} \times 15 \text{ kWh}/0.93$). Similarly, the gasoline price of one liter is usually between 7.5 RMB and 8 RMB; thus, the 100-kilometer fuel cost for CFVs is set as 50 RMB ($6.5 \text{ L} \times 7.5 \text{ RMB/L}$) and 60 RMB ($7.5 \text{ L} \times 8 \text{ RMB/L}$). The levels of the remaining vehicle attributes, including the cruising range, quick charging time, battery warranty, and emission standard, are based on Table 1 and Table 2. We adopt the approximate minimum and maximum values as the corresponding two levels.

3.3 Psychological attributes

Due to the eco-friendly characteristics of EVs, consumers are influenced not only by vehicle attributes but also by psychological attributes when making decisions on EV purchases. Although the TPB indicates that attitude, perceived behavioral control, SN, and PN are the main predictors for EV adoption behavior, due to overlap with vehicle attributes, these four psychological attributes cannot all be integrated into the choice models. Specifically, according to Zhang et al. (2018a)'s work, an individual's attitude towards EVs consists of three parts: perceived economic benefits, perceived risks, and PEB. Obviously, perceived economic benefits and perceived risks are closely related to some vehicle attributes, such as price, cost, charging time. Similarly, perceived behavioral control, which measures whether an individual can afford an EV, may be influenced by EV prices (Adnan et al., 2018). Different from attitude and perceived behavioral control, SN and PN reflect the perceived social and moral pressures

to perform or not to perform a certain behavior, respectively, so these two constructs can be clearly distinguished from vehicle attributes. With respect to some broader pro-environmental constructs, such as EA and PEB, they measure an individual's opinions towards the environment and the environmental benefits of EVs, respectively (Adnan et al., 2018; Kim et al., 2018), so they can also be distinguished from vehicle attributes. Based on the above reasons, we construct the BEV utility function that only includes EA, PEB, SN, and PN to avoid overlap with vehicle attributes. These four psychological attributes can be treated as sociodemographic variables that are constant for an individual but vary across individuals (Hensher et al., 2015). To measure their levels, we use a 12-item seven-point Likert scale (1 = “strongly disagree”; 7 = “strongly agree”), as shown in *Appendix B*.

3.4 Policy attributes

To promote EV adoption, the Chinese government has issued a series of policy instruments, such as purchase tax exemption (PTE), vehicle and vessel tax exemption (VVTE), rating and labeling programs (RLP), public information campaigns (PIC), driving restriction rescission (DRR), free parking (FP), free charging (FC), dedicated parking space (DPS), road toll exemption (RTE), and HOV lanes (Zhang et al., 2017). Motivated by Wang et al. (2017b), we divide the above policy instruments into three types: tax exemption instruments, information provision instruments, and convenience instruments, as shown in Table 3. Since some special policy instruments (e.g., DRR) are not implemented in all cities, and information provision instruments are difficult to quantify in the form of monetization, we use textual description to characterize different types of policy instruments and then provide respondents with several

common examples. Additionally, we do not consider the impact of purchase subsidies on EV adoption for the reason that the Chinese government intends to eliminate purchase subsidies after 2020 (Wang et al., 2017a),

Table 3 Classification of existing policy instruments implemented in China

Category	Definition	Examples
Tax exemption	Aims to lower the vehicle-related tax	PTE, VVTE
Information provision	Aims to provide EV-related information to consumers	RLP, PIC
Convenience	Aims to provide both use and financial convenience to consumers	DRR, RTE, FP, FC, DPS, HOV,

As described in Section 3.1, some market-oriented policy instruments, such as PCT and TDC, may be implemented in the future. In this case, annual PCT revenues/expenditures are related to three factors: power/gasoline consumption, the average driving distance, and the average carbon trading price. With an average annual mileage of 15,000 km (CATARC et al., 2018), the gasoline consumption equivalents are 563 L and 768 L for BEVs and 975 L and 1125 L for CFVs (where $1 \text{ kWh} \approx 0.785 \text{ kgCO}_2$ and $1 \text{ L gasoline} \approx 2.3 \text{ kgCO}_2^{2,3}$). If the initial carbon credits are set 10% below the current gasoline consumption status, namely, 931.5 liters of gasoline-equivalent ($0.9 \times 15000 \text{ km} \times 6.9 \text{ L}/100 \text{ km}$), and the average carbon trading price is 4 RMB per liter (Raux et al., 2015), then the annual PCT revenues of BEVs are nearly 1500 RMB ($((931.5\text{L} - 563 \text{ L}) \times 4\text{RMB}/\text{L})$) and 700 RMB ($((931.5\text{L} - 768 \text{ L}) \times 4\text{RMB}/\text{L})$), and the average value is 1100 RMB. Similarly, the annual PCT expenditures of CFVs are nearly 200 RMB ($((931.5\text{L} - 975 \text{ L}) \times 4\text{RMB}/\text{L})$) and 800 RMB ($((931.5\text{L} - 1125 \text{ L}) \times 4\text{RMB}/\text{L})$), and the average value is 500 RMB.

Annual TDC revenues/expenditures are related to two factors: the average number of trips

² <http://www.tanpaifang.com/tanjiliang/2013/1215/26997.html>.

³ <http://www.tanpaifang.com/tanjiliang/2013/1215/26998.html>.

and the driving credit price. In some Chinese cities, such as Beijing, Guangzhou, Chongqing, and Shenzhen, CFVs are restricted by the odd-even or tail number license plate restrictions, whereas BEVs are not (Yiche, 2018). Hence, for the initial driving credits, we assume that 4 driving credits per week will be allocated to CFVs, while 7 driving credits per week will be allocated to BEVs. As there are few data related to driving credit prices, we assume that the potential driving credit prices are between 10 RMB and 20 RMB, which is based on the airport high-speed charging standards in different cities (e.g., 10 RMB in Beijing and 20 RMB in Guangzhou). Considering the basic commuting needs of 5 working days per week, the annual TDC revenues of BEVs are 1040 RMB $((7 - 5) \text{ driving credit/week} \times 52 \text{ week} \times 10 \text{ RMB/ driving credit})$ and 2080 RMB $((7 - 5) \text{ driving credit/week} \times 52 \text{ week} \times 20 \text{ RMB/ driving credit})$, and the average value is 1560 RMB. Similarly, the annual TDC expenditures of CFVs are 520 RMB $((4 - 5) \text{ driving credit/week} \times 52 \text{ week} \times 10 \text{ RMB/ driving credit})$ and 1040 RMB $((4 - 5) \text{ driving credit/week} \times 52 \text{ week} \times 20 \text{ RMB/ driving credit})$, and the average value is 780 RMB.

Last but not least, we set up two choice scenarios to compare consumer preferences among the different types of existing policy instruments, PCT, and TDC, and to explore whether more revenues from PCT and TDC can always encourage consumers to buy EVs. Specifically, in scenario one, we highlight the assumptions that “...*in the future, there will be none or only one type of existing policy instruments or PCT or TDC...*”. In scenario two, we emphasize that “...*in the future, there will be only PCT and TDC, without any existing policy instruments...*”. According to these two scenario settings, all attributes and their levels are summarized in Table 4. Since a full factorial design would produce numerous choice sets, it is particularly important

to design a reasonable experiment to extract the most representative choice sets (Hidrué and Parsons, 2015). To this end, we use *Sawtooth Software*⁴ to generate 40 questionnaire versions, and each respondent is asked to finish one questionnaire version with 4 different choice tasks (see *Appendix A*). In particular, the first two tasks belong to scenario one, whereas the remaining two tasks belong to scenario two. In addition, each choice task contains one BEV option, one CFV option, and one non-chosen option (i.e., neither). Finally, the test design reveals that if there are more than 1000 respondents, then we can maximize *D-Efficiency*.

Table 4 Attributes and attribute levels in the choice experiment

		BEV levels	CFV levels
Vehicle attributes	Price: 10,000 RMB	20, 25	12, 17
	Cost: RMB per 100 km	10, 25	50, 60
	Cruising range: km	300, 500	1000
	Quick charging time: min	30, 60	
	Battery warranty	None, 8 years or 150,000 km	
	Emission standard		GB V; GB VI
Scenario one policy attributes	Policy instruments	None	
		Tax exemption (e.g., PTE, VVTE)	
		Information (e.g., PIC including safety, cruising range, and battery life)	
		Convenience (e.g., DRR, FP, HOV)	
		PCT (revenues: 1100 RMB per year for BEVs; expenditures: 500 RMB per year for CFVs)	
		TDC (revenues: 1560 RMB per year for BEVs; expenditures: 780 RMB per year for CFVs)	
Scenario two policy attributes	Annual PCT revenues/ expenditures: RMB	1500, 700	-200, -800
	Annual TDC revenues/ expenditures: RMB	2080, 1040	-1040, -520

Note: the level of psychological attributes is measured by a 12-item seven-point Likert scale.

⁴ <https://www.sawtoothsoftware.com/>

4. Data collection and characteristics

Our choice experimental survey was conducted via an internet-based survey platform named SO JUMP⁵ between March 28, 2019, and April 9, 2019. The respondents were private car owners or the population intending to buy a new car within three years. Before the formal survey, we invited 20 master's degree candidates and 40 MBA students to take a pretest to estimate the time for completing the questionnaire and to correct any unreasonable aspects of the design. Based on the pretest, the respondents needed at least 240 seconds. Hence, we retained only the data that took between 240 and 1800 seconds to complete the questionnaire. Moreover, respondents were asked to understand the two market-oriented policy instruments, and then, they needed to correctly answer the questions related to PCT and TDC (see *Appendix A*). In accordance with the above filtering rules, we ultimately obtained 1546 valid observations. The general sociodemographic characteristics are listed in Table 5.

First of all, nearly 97% of respondents own private cars, and 88.29% have intentions to purchase cars within three years. Moreover, the male respondents account for 56.21%, which is slightly higher than the female respondents. The majority of the sample is between 25 and 45 years old (over 71%); people in this age range are the most likely potential car buyers. The respondents are mainly from first-tier cities (45.92%), and most respondents (86.29%) are well-educated and have a bachelor's degree or above. It is worth noting that the population with a bachelor's degree (71.80%) is the main group of this survey, which is similar to the previous research (Huang and Qian, 2018; Li et al., 2018b; Wang et al., 2018; Wang et al., 2017a). In fact, compared to the individuals with associate degrees and below, well-educated populations

⁵ <https://www.wjx.cn/>.

usually have a higher annual household income that can afford a new car. The demographic characteristics of this survey also show that the majority of respondents can afford a new car because 91.46% of respondents have an annual household income of more than 100,000 RMB. Finally, 62.10% of respondents prefer PCT, 30.53% of respondents prefer TDC, and 7.37% of respondents choose neither.

Table 5 Sociodemographic characteristics of the survey sample

Sociodemographic variables		Frequency	Percentage (%)
Gender	Male	869	56.21
	Female	677	43.79
Age	25 and below	262	16.95
	26-35	629	40.69
	36-45	474	30.66
	46-55	170	11.00
	56 and above	11	0.71
Educational level	Associate degree and below	212	13.71
	Bachelor's degree	1110	71.80
	Master's degree	212	13.71
	Doctoral degree	12	0.78
Annual household income	Less than 100,000 RMB	132	8.54
	100,000-200,000 RMB	761	49.22
	200,000-300,000 RMB	444	28.72
	More than 300,000 RMB	209	13.52
City level	First-tier	710	45.92
	Second-tier	501	32.41
	Third-tier & below	335	21.67
Number of cars owned	0	47	3.04
	1	1345	87.00
	2 or more	154	9.96
Car purchase plan within 3 years	None	181	11.71
	Yes	1365	88.29
Policy instrument preference	Personal carbon trading scheme	960	62.10
	Tradable driving credit scheme	472	30.53
	Neither	114	7.37

Since the psychological attribute levels of respondents are measured by a 12-item seven-point Likert scale, it is necessary to evaluate the reliability and validity of the measurement.

Firstly, the Cronbach's alpha values of EA, PEB, PN, and SN are 0.587, 0.735, 0.769 and 0.796, respectively (*see Appendix B*), most of which exceed the threshold of 0.7 (Nunnally, 1978). Secondly, with respect to the validity of the measurement, the Kaiser-Meyer-Olkin (KMO) value is 0.869, and the level of significance is 0.000; thus, the data is suitable for factor analysis. The factor analysis results show that the cumulative variance is 59.91% after three principal components are extracted, with items SN1-3 and PN1-3 belonging to F1 and items PEB1-3 and EA1-3 corresponding to F2 and F3, respectively (*see Appendix B*). Therefore, we combine PN with SN and define a new psychological attribute, *norms*, which refer to both perceived social pressures and personal feelings of moral obligation to perform, or refuse to perform, a certain behavior.

5. Results

5.1 Model specification

Based on the random utility theory, the choice of the most valuable option among BEV, CFV, and neither can be regarded as a search process achieving utility maximization (McFadden and Daniel, 1986; Brownstone and Train, 1998). For a respondent, the utility of a choice (U) can be divided into an observable component (V) and an unobservable component (ε). In our case, the linear utility function can be expressed as follows:

$$U_{BEV} = V_{BEV} + \varepsilon_{BEV} = ASC_{BEV} + \beta_{BEV}X_{BEV} + \beta_{Policy}Y_{BEV} + \beta_{psychological}Z + \varepsilon_{BEV}$$

$$U_{CFV} = V_{CFV} + \varepsilon_{CFV} = ASC_{CFV} + \beta_{CFV}X_{CFV} + \gamma\beta'_{Policy}Y_{CFV} + \varepsilon_{CFV}$$

$$U_{Neither} = V_{Neither} + \varepsilon_{Neither} = \varepsilon_{Neither} \quad (1)$$

where the observable component depends on the alternative-specific constant (ASC), vehicle

attributes (X), policy attributes (Y), psychological attributes (Z) and associated coefficients including β_{BEV} , β_{CFV} , β_{Policy} , β'_{Policy} , and $\beta_{psychological}$. In particular, X_{BEV} includes five BEV vehicle attributes: price, cost, cruising range, quick charging time and battery warranty; X_{CFV} contains three CFV vehicle attributes: price, cost, and emission standard; Z represents psychological attributes including EA, PEB, and norms; It is worth noting that psychological attributes only appear in BEV utility function. This is because existing studies only point out that psychological attributes associated with EVs can promote EV adoption, but do not indicate the relationship between psychological attributes associated with EVs and the adoption of CFVs (Huang and Ge, 2019; Mohamed et al., 2018). γ is a dummy variable in which 0 represents scenario one, while 1 denotes scenario two. In addition, in scenario one, Y_{BEV} is a categorical variables including six different policy instruments setting, and Y_{CFV} is zero; in scenario two, Y_{BEV} and Y_{CFV} are continuous variables that represent the revenues and expenditures of PCT and TDC, respectively.

As the basic choice model, the MNL model needs to satisfy the independence of irrelevant alternatives (IIA) property, and the respondents are generally assumed to be homogeneous (Hausman and Mcfadden, 1981). However, in the context of EV adoption, consumers generally exhibit heterogeneous preferences (Liao et al., 2017). One way of relaxing the IIA property and reflecting preference heterogeneity is to adopt the RPL model by allowing the coefficient in the model to vary across respondents (Hensher and Greene, 2003). For these random parameters, both the mean and standard deviation are estimated based on predetermined probability distribution (Hensher et al., 2015). Hence, in this paper, we use the RPL model to reflect the preference heterogeneity among the respondents, and the probability (P) that the respondent

will select alternative i among all three alternatives can be described as follows:

$$P(i) = \int \frac{e^{V_i}}{\sum_{j=1}^3 e^{V_j}} f(\beta|\theta) d\theta \quad (2)$$

where $f(\beta|\theta)$ is the density function of β . In this paper, we first assume that all coefficients are normally distributed. Then, we change the distribution form by checking whether the estimation provides a significant standard deviation. Finally, we adjust the scrambled Halton sequences to maximize the simulated log-likelihood estimation.

5.2 Estimated results of scenario one

The estimated results of scenario one are shown in Table 6. As expected, most coefficients of BEV vehicle attributes are highly significant, except for the quick charging time. Specifically, the purchase price and power cost have a negative impact on consumers' willingness to adopt BEVs. Meanwhile, a longer cruising range and the battery warranty service will also increase consumers' BEV utility. Moreover, all psychological attributes, including EA, PEB, and norms, show a positive and strong impact on BEV adoption. It is worth noting that although the Cronbach's alpha value of EA is relatively weak (0.587), the impact of EA on BEV adoption is highly and positively significant. Thus, we still retain EA in BEV utility function. Finally, for CFV vehicle attributes, only the negative and highly significant effects of the purchase price are found.

Compared with the perfect competition scenario (i.e., no policy instruments in the future), all existing policy instruments and hypothetical market-oriented policy instruments can positively and highly affect consumer preferences for BEVs. From an overall perspective, the coefficients of PCT and TDC are higher than that of existing policy instruments. With respect

to the three types of existing policy instruments, convenience instruments have the highest coefficient. Although the coefficient of the TDC direct effect (2.18) is higher than that of the PCT direct effect (1.49), the interaction term between norms and TDC (-0.26) is negative; thus, the final positive effect of PCT (1.49) is higher than that of TDC (0.93, $2.18 - 0.26 * 4.81$) because the average value of norms is 4.81. This result implies that individuals will prefer PCT. In fact, according to our survey (see Table 5), 62.10% of respondents claim that they will prefer PCT instead of TDC.

Table 6 Estimated results of different scenarios

		Scenario One	Scenario Two
<i>Vehicle attributes</i>	<i>BEV_cons</i>	-3.57961***	<i>BEV_cons</i> -0.27274
	<i>Price_bev</i>	-0.07369***	<i>Price_bev</i> -0.14111***
	<i>Cost_bev</i>	-0.01320*	<i>Cost_bev</i> -0.01584**
	<i>Cruising range</i>	0.00132**	<i>Cruising range</i> 0.00160***
	<i>Quick charging time</i>	-0.00292	<i>Quick charging time</i> -0.00298
	<i>Battery warranty</i>	0.42183***	<i>Battery warranty</i> 0.30712***
<i>Policy attributes</i>	<i>Tax exemption</i>	0.61799***	<i>PCT_bev</i> 0.77467*
	<i>Information</i>	0.44667**	<i>TDC_bev</i> 0.74637*
	<i>Convenience</i>	1.05783***	
	<i>PCT</i>	1.49139**	
	<i>TDC</i>	2.17828***	
<i>Psychological attributes</i>	<i>EA</i>	0.34583***	<i>EA</i> 0.25517***
	<i>PEB</i>	0.37558***	<i>PEB</i> 0.25339***
	<i>Norms</i>	0.62908***	<i>Norms</i> 0.67398***
<i>Interaction term</i>	<i>Norms × PCT</i>	-0.16055	<i>Norms × PCT_bev</i> -0.16163*
	<i>Norms × TDC</i>	-0.26273*	<i>Norms × TDC_bev</i> -0.17787*
<i>Vehicle attributes</i>	<i>CFV_cons</i>	3.45714***	<i>CFV_cons</i> 3.62815***
	<i>Price_cfv</i>	-0.14660***	<i>Price_cfv</i> -0.14142***
	<i>Cost_cfv</i>	0.00744	<i>Cost_cfv</i> 0.00149
	<i>Emission standard</i>	-0.11686	<i>Emission standard</i> 0.06678
<i>Policy attributes</i>			<i>PCT_cfv</i> -0.05209
			<i>TDC_cfv</i> -0.1779
	Log-likelihood	-1939.04	Log-likelihood -1666.40
	McFadden Pseudo R ²	0.104	McFadden Pseudo R ² 0.097

Note: In scenario one, no policy instruments in the future is set as the reference case; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

5.3 Estimated results of scenario two

Except for the different choice scenario definitions, the main difference between scenario one and scenario two is the treatment of policy attributes. Specifically, policy attributes are treated as categorical variables in scenario one but as continuous variables in scenario two. Similar to scenario one, most vehicle and psychological attributes for BEVs, as well as the price attribute for CFVs, are found to have a significant influence, as shown in Table 6. Moreover, as expected, higher monetary revenues from PCT and TDC will promote the preference for BEVs. Another interesting finding is that the interaction terms between norms and PCT and between norms and TDC are negative, implying that individuals with higher norms will attach a low level of importance to higher monetary revenues from PCT and TDC. Last but not least, for CFVs, the effects of more monetary expenditures from PCT and TDC are non-significant, implying that the implementation of PCT and TDC will have less impact on the preference for CFVs.

6. Discussion

6.1 Interpretation of results

The main purpose of this study is to explore how consumers make trade-offs between different market-oriented policy instruments and how market-oriented policy instruments alter consumer's EV adoption behavior by influencing the psychological factors. According to the results of scenario one, we confirm the significant positive effects of PCT and TDC on individuals' EV adoption behaviors, which is a supplement and improvement to the present results of PCT and TDC. Specifically, the original literature related to PCT and TDC is primarily

intended to demonstrate that PCT and TDC can change individuals' energy consumption or personal car use intention or improving transportation system efficiency (Dogterom et al., 2018; Xu et al., 2017; Raux et al., 2015). Although Li et al. (2018b) and Li et al. (2019b) have pointed out the significant positive effect of PCT on individuals' EV adoption, they do not consider how consumers make trade-offs between different market-oriented policy instruments (i.e., PCT and TDC) and the role of psychological attributes in promoting EV adoption.

Even so, similar to the results of Li et al. (2018b) and Li et al. (2019b) who argue that the effect of PCT is upwards of that of most existing policy instruments (e.g., PTE, DRR, and charging discount), we find that individuals will prefer PCT and TDC to existing policy instruments. It indicates that policy instruments with multi-motivations (e.g. economic and psychological motivations) may be more powerful and effective. In addition, we also find that individuals will prefer PCT to TDC. The possible reasons for such preference are that first, as shown in *Fig. A1* and *Fig. A2*, the initial carbon credits for BEVs and CFVs are the same in PCT, whereas in TDC, the BEV owners can be obtained more initial driving credits than the CFV owners. Hence, PCT can better reflect the "fairness principle" and may be recognized by more people (Li et al., 2018a); second, recall that PCT and TDC are proposed from the perspective of carbon mitigation and relieving road congestion, respectively (Starkey, 2012; Zhao et al., 2018). Because PCT can better combine carbon mitigation issues with the eco-friendly characteristics of EVs (Li et al., 2019b), PCT may be favored by more people.

To further disclose the routes of PCT and TDC in promoting EV adoption, we set up scenario two. The results show that the effects of more revenues from PCT and TDC in promoting EV adoption are positively significant, which suggests that the first route for PCT

and TDC to promote EV adoption is similar to existing financial incentives, namely stimulating individuals' economic motivations (Wang et al., 2018; Wang et al., 2017b). In addition, we also find that three psychological attributes including EA, PEB, and norms have positive and highly significant effects on EV adoption, which is consistent with the results of past environmental psychology literature (Huang and Ge, 2019; Mohamed et al., 2018). This finding suggests that it is important to incorporate psychological attributes when making EV adoption decisions, and it also implies that policy instruments with some specific goals (e.g., PCT for carbon mitigation) may affect individuals' EV adoption behavior through psychological motivations (Li et al., 2019b). To verify such an effect, we further analyze the interaction between policy attributes and psychological attributes and find that norms negatively moderate the relationships between more revenues from PCT and TDC and EV adoption behaviors. This is because, as an expensive product, the purchase of EVs requires an individual to balance perceived moral (social) pressures and economic benefits (Cherchi, 2017). Therefore, an individual with higher norms is more likely to be influenced by his/her social groups and self-principles. On the contrary, individuals with lower norms will be motivated by more monetary revenues.

In addition to providing new insights into the role of PCT and TDC in promoting EV adoption, we also provide some explanations for changes in consumer attitudes towards vehicle attributes. First of all, although Li et al. (2018b) found that the quick charging time had a significant impact on EV adoption, their study was based on the assumption that the quick charging time was from 0.5 h to 2 h. Yet, the actual quick charging time has been shortened to less than 1 h. Therefore, we find that consumers do not perceive a significant difference between 0.5 h and 1 h of quick charging time. Moreover, compared with past work that declares the

importance of the fuel cost on consumers' vehicle purchasing decisions (Liao et al., 2017), we do not find a significant effect of the fuel cost on CFV adoption. The potential reason is that we focus on compact cars, which indicates that the cost discrepancy measured at RMB per 100 km among different CFVs is relatively low; thus, consumers may attach lower importance to the fuel cost. Finally, the potential reason for the non-significance of emission standard may be that only Guangzhou plans to implement the GB VI emission standard starting July 1, 2019 (CATARC et al., 2018), while most existing CFVs on sale meet the GB V emission standard; thus, consumers may pay less attention to this attribute.

6.2 Policy implications

To solve the dilemma of financial incentives in promoting EV adoption, in this paper, we suggest two market-oriented policy instruments, which can allow the government to shift the role from a traditional monetary provider to a regulator (Li et al., 2019a). Imagine that if we regard monetary flows as a system (see Fig. 2), then the economic benefits obtained by the EV owners can be regarded as outflows, and there are two ways for the government to provide inflows: first, the government adopts existing financial incentives and acts as a monetary provider; second, the government implements market-oriented policy instruments, where the government plays the role of a regulator, and the CFV owners act as monetary providers. In such a system, the government can control monetary flows in different pipelines by adjusting the magnitude of purple, blue, and green valves. For example, the government can directly adjust the number of subsidies to the EV owners (i.e., adjusting the purple and green valves) or change the initial credit line (i.e., adjusting the blue and green valves) to indirectly adjust the

distribution of the monetary between CFV owners and EV owners.

Since the long-term implementation of existing financial incentives will result in massive financial expenditures, the government will cancel financial incentives sooner or later, as shown by red “X” in Fig. 2. Such an adjustment may be at the expense of a sharp drop in sales of EVs (CATARC et al., 2018). However, different from existing financial incentives, the non-significant impact of CFV expenditures in the case of market-oriented policy instruments can ensure that there will always be inflows. Hence, the biggest advantage of market-oriented policy instruments is to reduce government financial expenditures while stabilizing the sales of EVs. Moreover, in market-oriented policy instruments, the blue and green valves shown in Fig. 2 represent the initial credit line set by the government for the CFV owners and EV owners, respectively. Since the number of credits consumed by different individuals in each compliance period varies and EV owners usually consume less, the government can adjust the distribution of benefits between CFV owners and EV owners through setting different initial credit line. In other words, as long as the government sets a reasonable initial credit line (i.e., adjusting the blue and green buttons in Fig. 2), market-oriented policy instruments can theoretically achieve the same economic benefits for EV owners as existing financial incentives. Finally, considering that countries around the world (e.g., the U.K. and Germany) have proposed a timetable for the ban on the sale of CFVs (CATARC et al., 2018), in the future, the government can still influence the supply and demand of EVs by implementing market-oriented policy instruments. Specifically, based on different annual driving mileage, the government can adjust the initial credit line to achieve the distribution of benefits among different EV owners. Hence, the implementation of market-oriented policy instruments is considered more sustainable.

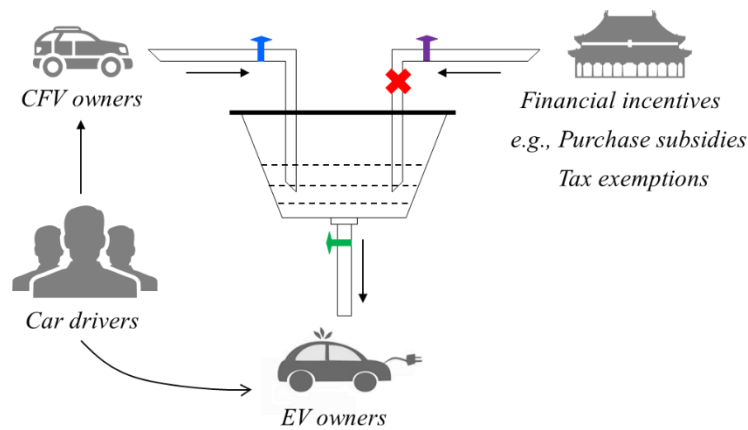


Fig. 2. The advantages of market-oriented policy instruments

Given these advantages, we suggest that in the future, the government should implement some market-oriented policy instruments to promote EV adoption. In the two potential market-oriented policy instruments, we argue that PCT may be a priority option because PCT not only has a more equitable initial credit allocation method but also can be combined with the eco-friendly characteristics of EVs. Therefore, PCT may be favored by more people. In addition, the government should carefully set the initial credit line to balance the relationships between revenues and expenditures of different individuals. This is because individuals with stricter norms will be driven more by social and moral pressures than by monetary revenues.

Finally, among the three types of existing policy instruments in China, convenience instruments are considered as the most effective alternative. Hence, policymakers should innovate the design of convenience instruments, such as setting up dedicated lanes for EVs (CATARC et al., 2018). Moreover, since psychological attributes including EA, PEB, and norms play an important role in promoting EV adoption, the government should also strengthen the design of information provision instruments to stimulate individuals' perceptions of the eco-friendly nature of EVs (Wang et al., 2017b). Furthermore, with technological advancement, consumer concerns over the quick charging time are gradually decreasing. Hence, more

investment and innovation should focus on other aspects, such as extending battery warranty services, improving the cruising range, and evolving the business model (Helveston et al., 2019; Bohnsack et al., 2014).

6.3 Limitations and future research

Despite the major contributions of this study, several aspects warrant further research. First, we consider only the impact of EA, PEB, and norms in BEV utility function, and thus, more psychological attributes can be incorporated in the future. For example, *consumer innovativeness* measures the tendency of consumers to purchase and to adopt new products instead of sticking to previous products (Heidenreich et al., 2017). Hence, individuals with higher *consumer innovativeness* may be more concerned with the innovation of the EV itself rather than the effect of policy instruments. Another interesting psychological attribute is *affect*, which has been confirmed as an important indicator of car use intention (Steg and Vlek, 2009). Therefore, it is an attractive topic to explore whether policy instruments with multiple motivations can strengthen the link between *affect* and EV adoption behavior.

Moreover, we have empirically pointed out that PCT and TDC can achieve the same effect as existing financial incentives as long as the government sets reasonable carbon credits and driving credits line. However, we do not reveal how to design such a reasonable initial credit line. Therefore, establishing a mathematical model to simulate the trading process among different consumers will provide important implications for the government to design the optimal initial credit line. Finally, our study does not consider the decision process of EV manufacturers. Embedding the consumer utility function into the EV manufacturers' demand

and establishing a decision system that includes enterprises, consumers and the government will provide a more comprehensive understanding of the diffusion of EVs.

7. Conclusions

With the maturity of the market mechanism, there are growing calls for policy instruments to shift from government to market (Xu and Su, 2016). In this paper, we suggest two market-oriented policy instruments (i.e., PCT and TDC), which can allow the government to shift the role from a monetary provider to a regulator. Our research shows that these two market-oriented policy instruments can stimulate consumers' both economic and psychological motivations, and are more powerful than existing policy instruments. We hope that these findings can assist policymakers in designing novel policy instruments to promote EV adoption. In addition, through the analysis of the interaction between policy attributes and psychological attributes, it is also our hope that we can provide new insights into how policy instruments with multi-motivations can change consumer behaviors through psychological factors.

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Appendix A

Description of the two schemes as they appeared to the respondents

With the elimination of purchase subsidies for electric vehicles, two emerging policy instruments are likely to take over in the future. The relevant descriptions are as follows:

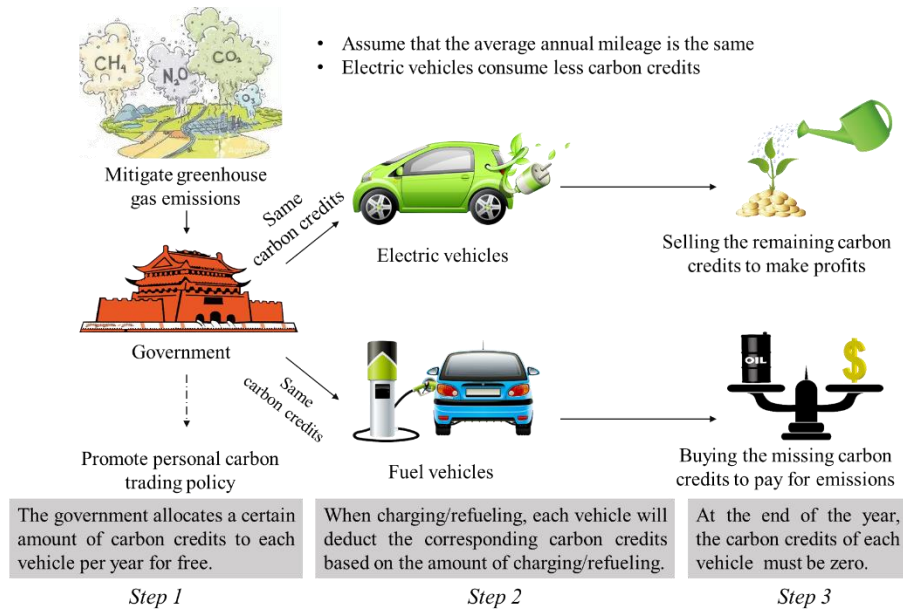


Fig. A1. Description of the PCT scheme

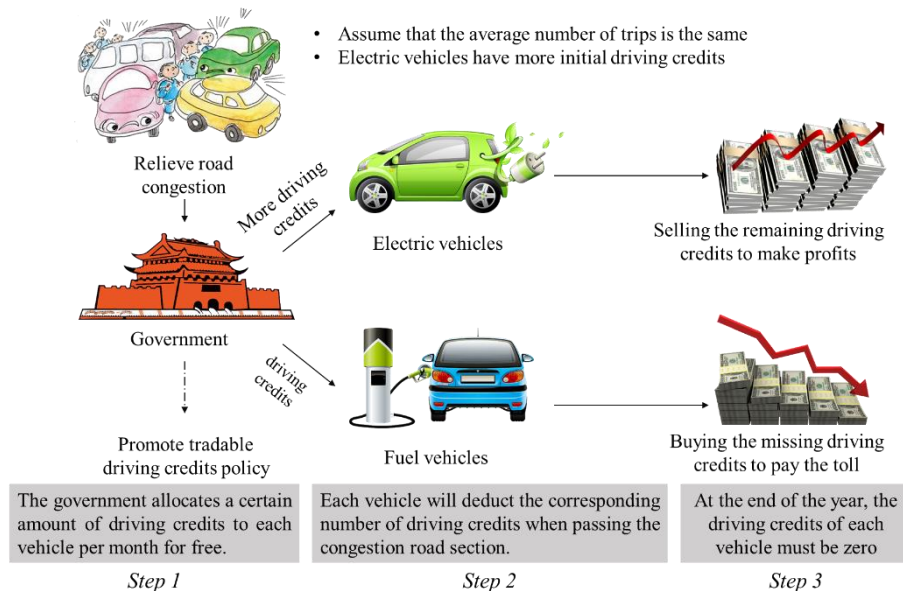


Fig. A2. Description of the TDC scheme

Q1: Do you understand the above two emerging policy instruments?

Yes

No (Submitted as invalid)

Q2: With the same average annual mileage, driving a CFV is more likely to benefit from the

PCT scheme than driving a BEV.

True

False (Correct answer)

Q3: With the same average number of passes per month, driving a BEV is more likely to benefit from the TDC scheme than driving a CFV.

True (Correct answer)

False

Example of scenario one

Assuming that the license plates of EVs and CFVs do not need to be obtained by means of "auction" or "lottery", and the down payment for the vehicle loan is the same. *In the future, there will be none or only one type of existing policy instruments or PCT or TDC.* If your annual driving mileage is 15, 000 kilometers, and the charging infrastructures have been improved, and the vehicle appearance, brand, interior space, and other factors have met your expectations, which type of vehicle would you want to choose?

Attributes	EV	CFV
<i>Price: 10, 000 RMB</i>	25	12
<i>Cost: RMB per 100 km</i>	10	60
<i>Policy instruments</i>	Tax exemption (e.g., PTE, VVTE)	None
<i>Emission standard</i>		GB V
<i>Cruising range: km</i>	500	
<i>Quick charging time: min</i>	60	
<i>Battery warranty</i>	None	
Please choose the most valuable option:	<input type="checkbox"/>	<input type="checkbox"/>
	<input type="checkbox"/> Neither	

Example of scenario two

Assuming that the license plates of EVs and CFVs do not need to be obtained by means of "auction" or "lottery", and the down payment for the car loan is the same. *In the future, there will be only PCT and TDC, without any existing policy instruments.* If your annual driving mileage is 15, 000 kilometers, and the charging infrastructures have been improved, and the vehicle appearance, brand, interior space, and other factors have met your expectations, which type of vehicle would you want to choose?

Attributes	EV	CFV
Price: 10, 000 RMB	20	17
Cost: RMB per 100 km	25	50
Annual PCT revenues / expenditures: RMB	700	-200
Annual TDC revenues / expenditures: RMB	1040	-1040
Emission standard		GB VI
Cruising range: km	500	
Quick charging time: min	30	
Battery warranty	8 years or 150, 000 km	
Please choose the most valuable option:	<input type="checkbox"/>	<input type="checkbox"/>
	<input type="checkbox"/> Neither	

Appendix B

Table B1 Description of the measurement items in the questionnaire

Construct	Measurement items	Cronbach's alpha	Source
Environmental Awareness (EA)	EA1: Humans must live in harmony with nature in order to survive (mean: 6.631; S.D.: 0.660). EA2: I am concerned about human behavior and its influence on climate change and the environment (mean: 6.032; S.D.: 0.890). EA3: I think people should change their behavior to reduce climate change and protect the environment (mean: 6.332; S.D.: 0.811).	0.587	(Engelken et al., 2018; Korcaj et al., 2015)
Perceived Environmental Benefits (PEB)	PEB1: Compared to CFVs, EVs help in responding to global warming via emissions reduction (mean: 6.147; S.D.: 1.023). PEB2: Compared to driving a CFV, driving an EV constitutes a contribution to social responsibility for the environment (mean: 5.842; S.D.: 1.082). PEB3: Compared to purchasing a CFV, purchasing an EV indicates more care for the environment (mean: 5.686; S.D.: 1.123).	0.735	(Kim et al., 2018; Carley et al., 2013)
Personal Norms (PN)	PN1: Due to my personal values, I feel obliged to purchase an EV instead of a CFV (mean: 5.488; S.D.: 1.209). PN2: No matter what others think, I feel that I should purchase an EV instead of a CFV (Mean: 4.958; S.D.: 1.315). PN3: I would feel guilty if I purchased not an EV but a CFV (mean: 3.874; S.D.: 1.371).	0.769	(Zhao et al., 2019; Bamberg et al., 2007)

Subjective Norms (SN)	SN1: Many people who are important to me own an EV or are considering purchasing an EV instead of a CFV (mean: 4.753; S.D.: 1.408).	0.796	(Han et al., 2019; Du et al., 2018; Klockner et al., 2013)
	SN2: Many people who are important to me would give me their approval for purchasing an EV instead of a CFV (mean: 4.928; S.D.: 1.313).		
	SN3: Many people who are important to me would want me to purchase an EV instead of a CFV (mean: 4.736; S.D.: 1.395).		

Table B2 Component matrix of the factor analysis of the 12 questionnaire items

	Component		
	F1	F2	F3
SN3	0.828	0.119	0.098
SN2	0.816	0.114	0.084
SN1	0.744	0.007	0.031
PN2	0.647	0.417	0.081
PN3	0.583	0.419	-0.005
PN1	0.519	0.478	0.175
PEB2	0.133	0.780	0.190
PEB1	0.069	0.757	0.170
PEB3	0.238	0.739	0.072
EA1	-0.038	0.074	0.771
EA3	0.076	0.145	0.756
EA2	0.173	0.154	0.656

Note: Total variance explained =59.91%; KMO =0.869; Bartlett's Test Chi-sq =5941.231, df =66, p < 0.000, N = 1546.