

**VEHICLE OWNERSHIP TRANSITION AND
SUSTAINABILITY IMPACTS IN CHINA**

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ABSTRACT

With considerable economic growth and technology development, China is rapidly experiencing motorization and a dramatic expansion of the transportation system. This dissertation centers on exploring vehicle ownership in China with new transportation technology influencing, and addresses the sustainability implications. First, it examines household vehicle purchase decisions across 59 cities in China with broad geographic, environmental, and socio-economic characteristics, focusing on a subset of households who own e-bikes and relying on a telephone survey from an industry customer database. Second, this dissertation presents a study on public perceptions and purchase intention towards new energy vehicles (battery electric vehicles and plug-in hybrid electric vehicle), and discusses factors influencing new energy vehicle purchase and illustrates policy implications, using an intercept survey in Beijing. Third, this dissertation reveals daily use patterns and users' experience of an emerging transportation mode (micro electric vehicle) in China using a semi-structure interview. Users' purchase decision, mode choice, safety perception, vehicle status, and future usage are discussed. Lastly, a behavioral life cycle assessment (LCA) model that includes explicit, probability-based behavioral inputs that influence choices in the LCA process is built. Furthermore, an LCA model for transportation system for China is developed using China's manufacture inventory data.

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CHAPTER 1
INTRODUCTION AND GENERAL INFORMATION

1.1 Introduction

China has seen unprecedented increases in motorization in the past decade, and will continue to see growth in vehicle ownership and use. While economic growth and the rising middle class influence this motorization trend, there are several factors that make this new motorization trend stand out from historical increases in motorization in the West; both of which have significant sustainability implications. First, relatively strict land use control, significant urban density, and congestions could reduce auto ownership and/or use, implying that vehicle ownership and use patterns might not follow western patterns. The second major factor is that vehicle technology is rapidly changing and China's auto industry is poised to adopt new energy fuels and vehicles. As China moves into uncharted territory in regard to motorization, it is more critical than ever to understand the motorization dynamics in the context of socio-demographic, urban form, and environmental constraints. Understanding these factors, in the Asian context, will assist policy makers in developing appropriate regulations or incentives that encourage judicious purchase and use of vehicles of various types and contribute to decision makers overall grasp of market demand. The unprecedented increases in motorization is also countered by a quest for sustainability. Understanding the sustainability implications of motorization, especially understanding the effects of policy or technology changes on environmental impacts would play an important role in policy making and promotion.

This dissertation centers on exploring vehicle ownership in China with new transportation technology influencing, and address the sustainability implications. The studies for the dissertation can be classified into two parts. The first part includes developing choice models to estimate factors influencing vehicle purchase and use patterns in China with rapid changing new vehicle technology and adaptation alternative fuels. The second main research activity focuses on developing a behavior related life-cycle impact assessment (LCA) model, and an LCA model for China transportation system, to evaluate energy consumption and emissions of mode choice and use.

In the dissertation, four studies have been conducted. Study one (Chapter 2) examines household vehicle purchase decisions across 59 cities in China with broad geographic, environmental, and socio-economic characteristics, focusing on a subset of households who own e-bikes and relying on a telephone survey from an industry customer database. Study two (Chapter 3) examines public perceptions and purchase intention towards new energy vehicles (battery electric vehicles and plug-in hybrid electric vehicle), and discusses factors influencing new energy vehicle purchase and illustrates policy implications, using an intercept survey in Beijing. The third study (Chapter 4) reveals daily use patterns and experience of an emerging transportation mode in China, micro electric vehicles, using a semi-structure interview with micro electric vehicle owners. A series of questions are answered in qualitative and quantitative ways including purchase decision, mode choice, safety perception, vehicle status, and future usage. In the last study (Chapter 5), a new approach named Behavioral life cycle assessment (LCA) that includes explicit, probability-based behavioral inputs that influence choices in the LCA process is developed. Also, an LCA model for transportation system in China is developed using manufacture inventory data in China.

CHAPTER 2
FACTORS INFLUENCING MOTORIZATION OF E-BIKE USERS
ACROSS CHINA

This chapter presents a modified version of a research paper by Ziwen Ling, Christopher R. Cherry, Hongtai Yang, and Luke Jones titled “From e-bike to car: a study on factors influencing motorization of e-bike users across China” published on Transportation Research Part D: Transport and Environment in 2015.

Abstract

Household car ownership has risen dramatically in China over the past decade. At the same time a disruptive transportation technology emerged, the electric bike (e-bike). Most studies investigating motorization in China focus on macro-level economic indicators like GDP, with few focusing on household, city-level, environmental, or geographic indicators, and none in the context of high e-bike ownership. This study examines household vehicle purchase decisions across 59 cities in China with broad geographic, environmental, and socio-economic characteristics. The author focuses on a subset of households who own e-bikes and rely on a telephone survey from an industry customer database. According to these responses, the author estimates two three-level hierarchical choice models to assess attributes that contribute to 1) recent car purchases and 2) the intention to buy a car in the near future. The results show that the models are dominated by household characteristics including household income, household size, household vehicle ownership, number of licensed drivers and duration of car ownership. Some geographic, environmental and socio-economic factors have significant influences on car purchase decisions. Only two city-level transportation variables have an effect – higher taxi density and higher bus density reducing car purchase. Cold weather, population density gross domestic product per capita positively influence car purchase, while urbanization rate reduces car purchase. Because of supply heterogeneity in the data set, described by publicly available urban transportation data, this is the first study that can include geographic and urban infrastructure differences that influence purchase choice and suggests potential region-specific policy approaches to managing car purchase may be necessary.

1.1 Introduction

China's considerable economic growth over recent decades has been accompanied by a dramatic expansion of its urban transportation systems, with increases in motorization (In this paper, motorization means that households transition from relatively smaller- or non-motorized vehicle to heavier motorized vehicle), and rapid development of road infrastructure and transit. One of the most substantial developments is a surge in ownership of private vehicles – specifically cars, and in the past decade, electric bikes (e-bikes). Since 1998, nearly 90 million cars, nearly 200 million e-bikes and nearly 200 million motorcycles (including gasoline-powered scooters) have been sold in China, shown in Figure 2.1 (Weinert et al. 2008, National Bureau of Statistics 2012a, Jamerson et al. 2013b). In 2009, China became the largest passenger car market in the world, exceeding sales in the USA for the first time (Huo et al. 2012a). By 2050 the sales of private light-duty passenger vehicles in China could reach 23-42 million and the total vehicle stock could be as large as 530-623 million (Huo et al. 2012b). Hence, China's motorization presents transportation, energy, and environmental challenges on a global scale, and is of great interest to a wide audience of policy-makers and researchers.

E-bikes have grown in popularity over the past decade in China, and are now a substantial portion of the transportation system in most urban areas. About 30 million are sold annually and an estimated 150 million or more are on the road today (Jamerson et al. 2013b). E-bikes constitute a spectrum of designs from bicycle style e-bikes (BSEB) to scooter style e-bikes (SSEB) (Figure 2.2); all are semi-motorized two wheel vehicles that operate on human (pedal) and battery-electric power. The rapid adoption of e-bikes across China has been notable, with the earliest market entries occurring in the late 1990's, followed by swift expansion in the early- to mid-2000's, outpacing car growth. The mid-2000's were characterized by hundreds of market entrants as e-bike manufacturers and suppliers attempted to establish themselves in the rapidly growing market (Weinert et al. 2007c). The late 2000's and early 2010's saw a stabilized e-bike market with 20-30 million sold yearly and a few larger companies beginning to establish

market dominance. The boom of e-bikes was triggered by Chinese government's effort to restrict motorcycles, economic development, and publicity of e-bikes as zero-emission vehicles (Cherry et al. 2009, Yang 2010). There has been some scrutiny on safety and environmental impacts of e-bikes. The burden of injury of e-bikes has been increasing (Feng et al. 2010) and they experience many conflicts with cars at intersections (Bai et al. 2013). Focusing on e-bike's environmental impacts, Cherry et al. (2009) compared environmental impacts of electric bikes to buses and motorcycles in China pointing out most pollutants are lower than or on the same level of bus emissions except SO₂. From the geographic view, provinces in Southern China have lower emission rates (partial hydro power generation) of electric bikes than provinces in the North (almost solely coal power generation).

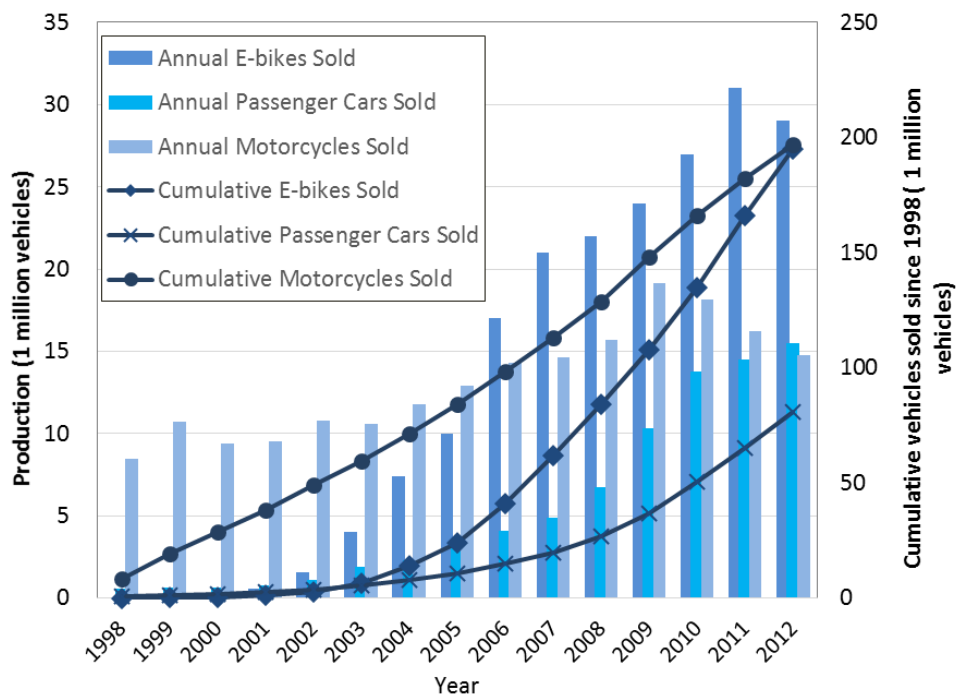


Figure 2.1. Vehicles Sold Since 1998 in China

Bicycle Style Electric Bike



Scooter Style Electric Bike



Figure 2.2. Electric bike design variations (adapted from Cherry et al. 2007)

An important question that remains unanswered is how the rapid and large adoption of e-bikes may disrupt China's traditional motorization pathway. There are some suggestions that e-bikes could either hasten or delay the transition to private car ownership within households (Cherry et al. 2015). Understanding e-bikes' role in the transition through modes of transportation is important for policy-makers seeking a sustainable trajectory for China's motorization, yet there has been little research on this topic. There has been no systematic cross-city comparison of e-bike and car ownership at the individual household level, particularly comparing areas with different cultural, topographic, economic, and environmental geographies. This paper begins to fill an important gap by investigating trans-geographical influences on the decision to purchase a personal car, particularly among e-bike owners who have adopted this semi-motorized personal transportation mode.

Focusing on the role of e-bikes in motorization and urban transportation, the author surveyed 947 e-bike owners across 59 Chinese cities. The author estimates two models for this key subset of total transportation system users, one to assess factors influencing recent car purchases and one to assess factors influencing the intention to purchase a car

in the near future. Both models aim to identify the determinants that influence motorization from e-bike to car. One key distinction with this approach, compared to others, is that the author focuses on geographic and environmental differences. The important contribution is that this paper begins to provide disaggregate cross-city analysis, compared to other studies that focus on individual cities (Weinert et al. 2007d, Montgomery 2010, Cherry et al. 2015). The remainder of the paper is organized as follows: section 2 discusses the previous studies on mode shift and behavior in China and vehicle ownership. Section 3 discusses methodology and data used in the study. Section 4 presents the results and discussion on vehicle ownership. Section 5 presents conclusions and limitation of this study.

2.1 Background

2.1.1 Mode shift and behavior

In a rapidly changing economic and regulatory environment, the role of e-bikes in sustainable motorization is not clear. E-bikes are not simply replacing bicycles. Assessing counterfactual modes and ultimately the influence of e-bikes on motorization is important to understand their relative impact on the transportation system (i.e., environment, safety, and operations). There have been only four studies in four cities that assess the role of e-bikes in motorization and mode choice in China. First, Cherry et al. (2007a) investigated e-bikes in competition with bicycles in Kunming and Shanghai. They found that both cities had similar mode choice characteristics. Most e-bike riders (50-60%) were diverted from bus transit modes followed by (10-20%) diverted from a bicycle. Car or taxi diversion constituted 10-15%. A follow-up study by Cherry et al. (2015) used a similar sampling approach for four datasets spanning 2006-2012 in Kunming, China. The authors found that e-bikes were still displacing a large amount of bus transit (>50%), but over that time, car ownership increased by nearly 100% and bicycle ownership dropped in half. One quarter of e-bike trips in 2012 were diverted car-based modes and just 8% of e-bike trips were diverted from bicycles. The role of e-bikes (in 2009) in Jinan mirrored Kunming. Bus was a substitute for 65% of e-bike trips and bicycle was a substitute for

only 13% of trips. Car-based mode was a substitute for 12% of trips (Montgomery 2010). Findings from these three studies contrast findings from Shijiazhuang (in 2006), where just one third of e-bike riders were displaced bus riders and over 60% of respondents would shift to bicycle (Weinert et al. 2007d). Figure 2.3 shows the relative displaced modes derived from those studies.

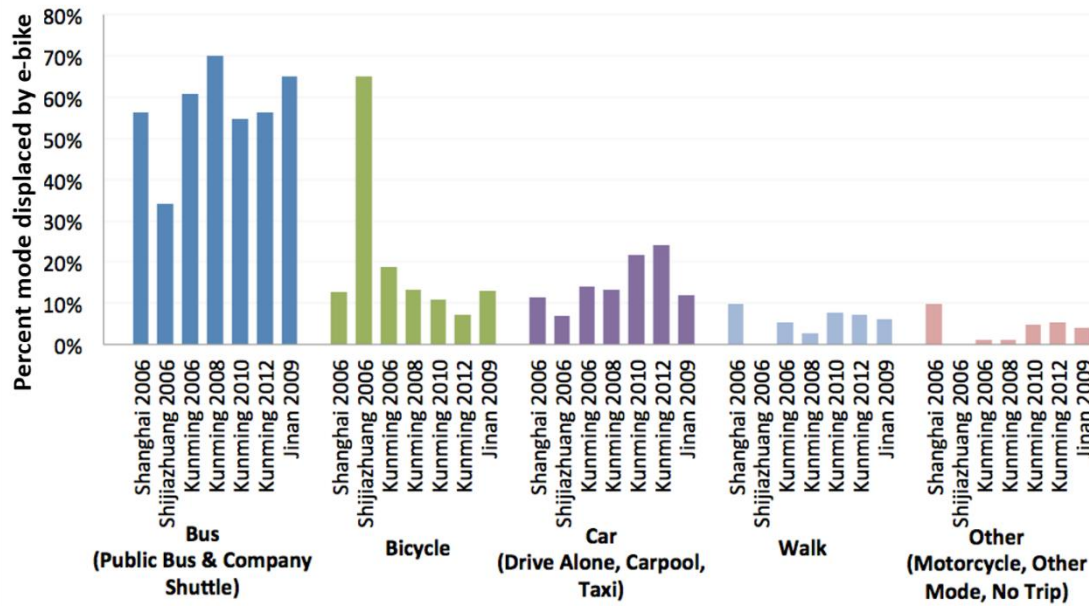


Figure 2.3. Previous e-bike studies and potential mode shift.

2.1.2 Previous vehicle ownership research

Many recent studies have modeled car ownership decisions in Asia. Most literature can be broadly categorized as macro-level economic studies at the national or regional level and micro-level household vehicle choice models.

National or regional level studies focus on macroeconomic indicators, such as the strong relationship between per capita gross domestic product (GDP) and car ownership, some including energy or space constraints. Many of these studies speculate on how China's motorization could follow other trends, developing long-term vehicle ownership

scenarios, particularly in the context of China's urban space constraints (Huo et al. 2007, Ng et al. 2010, Wang et al. 2011, Huo et al. 2012a, Wang et al. 2012).

A few researchers have attempted to model motorization and purchase decisions at the individual or household level in China (Ni et al. 2010). Two recent studies investigate the joint ownership decisions of motorcycle and car ownership, finding that the ownership of motorcycles and overall household fleet composition has significant influence on car ownership (Chiou et al. 2009, Anastasopoulos et al. 2012). Some recent work finds that car restriction policies can be very effective at reducing car ownership (Chen et al. 2013b). Our study investigates household level purchase choices and the author draws from past literature on the expected direction of effects.

- Urbanized areas: higher urbanized areas trend to have lower multiple household car ownership (2 or 3 cars) (Chiou et al. 2009). Chamon et al. (2008) found that higher urbanization levels yielded lower car ownership rates.
- Population density: lower population density yields lower car ownership rates (Chamon et al. 2008, Flamm 2009).
- Road density: high road density encourages car ownership (Chiou et al. 2009).
- Transit density: increased transit service reduces car ownership (Chiou et al. 2009).
- The number of employed family members: more working members of a household results in higher levels of household car ownership (Chiou et al. 2009, Musti et al. 2011).
- The number of family members aged below 18: literature contains mixed findings on the effect of number of children. Ben-Akiva and Lerman (1974) concluded that the number of household members aged below 10 years old may negatively affect car ownership since children may increase family expense and decreased disposable income. However Chiou et al. (2009) and De Jong (1990) showed that increasing numbers of children will increase the demand of car ownership.

- The number of motorcycles in household: one study indicated that the number of motorcycles has a significantly negative effect on the car ownership. Also, the researchers showed that there is high substitution effect between cars and motorcycles within a household (Chiou et al. 2009). However, Chen et al. (2013a) found out that households already owning motorcycles are more likely to buy a car.
- The number of licensed drivers in household: The number licensed drivers has a significant and positive effect on car ownership (Chu 2002, Chiou et al. 2009, Flamm 2009).
- Income: Higher income is widely identified as the primary factor in increased vehicle ownership (Button et al. 1993, Chu 2002, Zhao et al. 2002, Dargay et al. 2007, Ni 2008, Potoglou et al. 2008, Flamm 2009, Chen et al. 2013a).
- Gross domestic product per capita: Per capita GDP has a known and strong positive correlation with increasing automobile ownership (Chamon et al. 2008).

The studies presented above often omit social factors, varied built environment, environmental variables, policy, or geography when constructing vehicle choice models. This study includes most of the variables included in previous studies and extends those to include several other variables. Figure 2.4 breaks down the data framework into two main variable categories, city level data and household level data. City level data includes geographic factors that include environmental variables, transportation variables, and socio-economic variables.

In order to analyze the effects of various factors on vehicle ownership, researchers have applied various statistical models primarily categorized as discrete outcome disaggregate models and aggregate continuous models (Potoglou et al. 2008). Disaggregate models tend to use household as the basic unit of analysis. While, aggregate models explain vehicle ownership as an ownership rate at the region/zone level (Potoglou et al. 2008). Most models estimate vehicle ownership level at a specific time and point, while some

dynamic models were developed to predict how household vehicle would be changed in response to future changes in vehicle and household characteristics (Chu 2002).

To the author's knowledge, no study has been conducted to comprehensively analyze different demographic, built environment, and geographic factors' effects on car ownership and purchase in China, particularly focused on e-bike owner's decision to purchase a car.

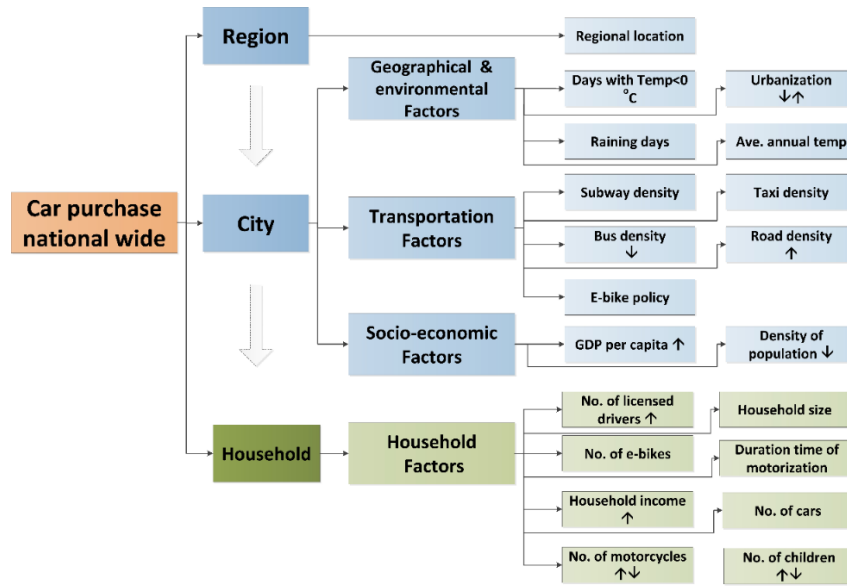


Figure 2.4 Data framework for car purchase model. Arrows indicate direction of influence on car purchase and ownership from literature.

2.2 Methods and Data

2.2.1 Survey and City Data

The dataset used in this survey was sampled from a nationwide e-bike manufacturer customer database that includes contact information of over two million e-bike purchasers over a decade. The author identified 59 cities from the database that represent large, medium, and small cities in most of China's 31 administrative regions. Cities were chosen based on their population and relative size compared to other cities in the province or region. They were also chosen based on their classification and availability of

consistently reported and publicly available data on infrastructure, economic, and meteorological indicators. Because the author relies on an industrial customer dataset, sample is limited to cities in the company's market. In total, 947 complete samples were collected from a dataset spanning 2003-2012 (each sample was collected from one household). The sample was limited to the most recent five years to assure reliable contact information. On average, the author samples 16 respondents from each city (range: 1-37). Figure 2.5 shows the sampled cities by circles whose size represents the number of sampled respondents, circle color represents the number of cars per 1000 residences (light to dark, range: 10-380), population density is represented by the shaded map, and China's seven regions are labeled. Denser populations are along the east coast. Generally, cities sampled on the east region had higher motorization rates than more central regions in our sample. The sample represents some of the most populous areas of China. The sampling approach randomly identified respondents in the dataset in the appropriate cities and called the number listed. After an introduction, surveyors conducted a phone interview, querying the respondent's demographics, vehicle ownership, ownership history, purchase intentions, preferences, and a short travel diary.

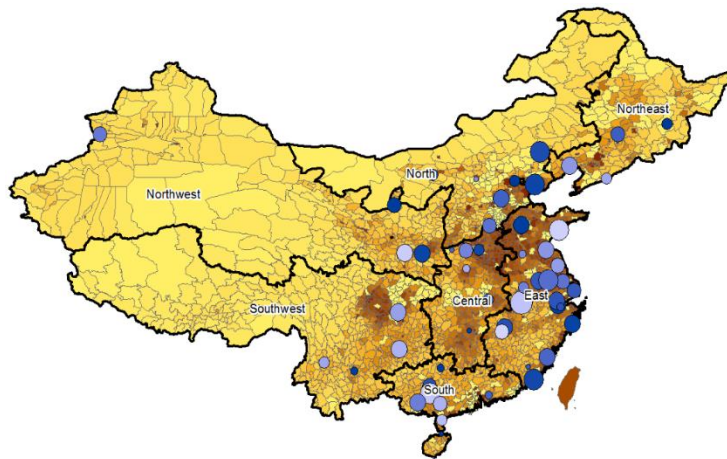


Figure 2.5. Geography of survey sample.

(Higher population density are darker shaded areas. Surveyed cities represented by blue dots and dot size is proportional to number of surveys in that city (range: 1-37). The darker dots represent cities with higher per

capita personal car ownership (range: 10-380 cars per 1000 people). Seven regions are outlined and labeled.)

The response rate was 70%, however, after cleaning data and discarding grossly incomplete surveys, the final response rate was 47% (the final sample size is 947). Males and females rejected our survey at the about same rate as the sample population. Key survey indicators are shown in Table 2.1, tabulated across China's seven regions (shown in Figure 2.5).

Data from the interview are supplemented by publicly available statistical data from the city (National Bureau of Statistics 2012a). Weather data were gathered from Weather Underground (2013).

2.2.2 *Car ownership model*

Two models of households' choice of car ownership from 2011 to 2013 and purchase intention for 2014 are proposed (Figure 2.6). The first model focuses on revealed car purchase in the past two years. This model relies on vehicle purchase history and categorizes those who purchased a vehicle and those who did not. This model does not necessarily imply that those who purchased a vehicle still have that vehicle (though none of our respondents reported ridding themselves of the purchased vehicle in that short time). The author estimate factors that influence purchase choice with a hierarchical logit choice model.

A separate car purchase intention model is developed on the same hierarchical logit model framework, estimating attributes that influence the intention to purchase a car in the next year. According to the survey results, 21.4% of respondents intended to purchase a car from 2013 to 2014, which is a significantly higher rate than past years (5% purchased a car from 2012 to 2013). According to the transaction history, the average number of cars purchased per household over the span from 2011 through 2013 is nearly 18% (less than the intended number of purchases in the coming single year). This calls to

question the realism of intended purchase plans compared to executed purchases and is a limitation of this and other aspirational stated preference approaches.

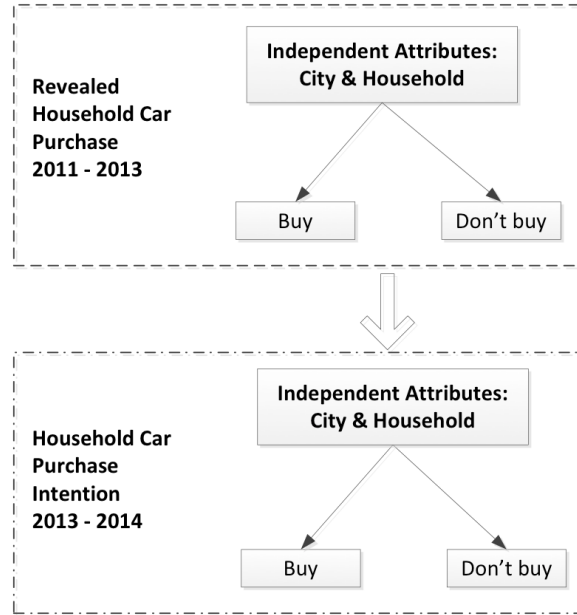


Figure 2.6. Framework of the vehicle purchase models

2.2.3 Hierarchical logit model

The author expects factors described in the survey and factors developed from each city to influence the motorization pathway and ultimately the car purchase behavior of respondents. The data used in this study were organized into three levels to reflect the natural hierarchy of the data, as shown in Figure 2.7. Level 1 is the household level with 947 respondents collected nationwide. Level 2 is the city level with 59 cities the author chose from the manufacturer's database and Level 3 includes seven regions. Household-level characteristics correspond to household factors in consisting of number of household cars, number of licensed drivers, number of household e-bikes, duration of the first motorized vehicle ownership, household income, and others. City-level

characteristics consist transportation factors including road density, e-bike policy, bus density, taxi density, and subway density. Socio-economic factors include GDP per capita, population density, and urbanization. Geographical and environmental factors include days with precipitation, and days with temperature below 0 °C. Regional-level has dummy variables to indicate one of the seven regions in China.

The revealed household car purchase y_{ij} is a binary response for household i in city j of region k . The probability of car purchase equals one as $p_{ijk} = \Pr(y_{ij}=1)$ and p_{ijk} was modeled using a logit link function.

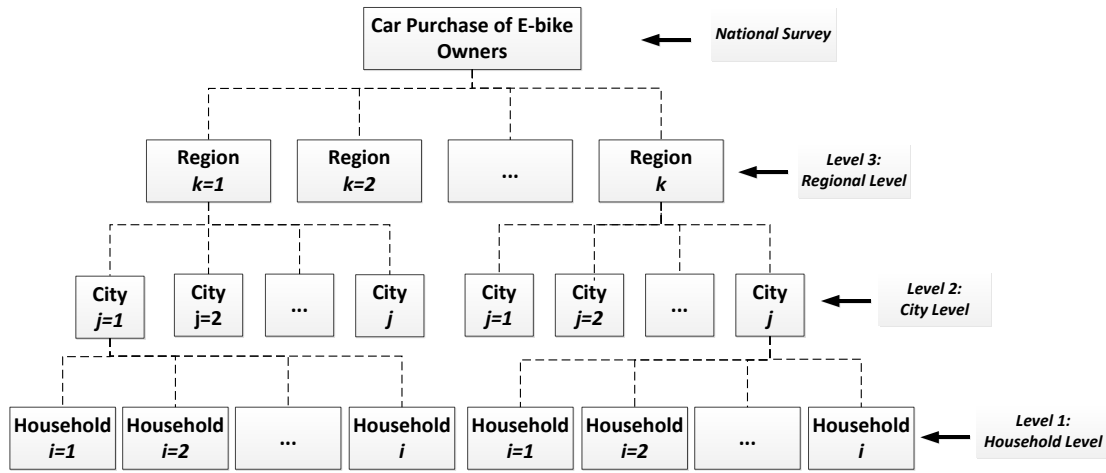


Figure 2.7. Hierarchical data structure

The three-level hierarchical model for binary data is written as:

$$\text{Logit}(P_{ijk}) = \log\left(\frac{P_{ijk}}{1-P_{ijk}}\right) = \beta_0 + \sum_{m=1}^M \beta_m X_{m_{ijk}} + \sum_{n=1}^N \beta_n X_{n_{jk}} + \sum_{q=1}^Q \beta_q X_{q_k} + U_{jk} + U_k \quad (1)$$

Where p_{ijk} is the probability of car purchase of household sample i (level 1) in city j (level 2) of region k (level 3). X_{ijk} , X_{jk} , X_k are respectively household, city, and region features to which correspond the fixed effects, while β_m , β_n and β_q is the intercept of the model. U_{jk} and U_k represent city level random effect and region level random effect. Estimation of these two parameters allows modeling the correlations

between households of the same city and between cities of the same region. They are independent and assumed to be normally distributed: $U_{jk} \perp U_k$, $U_{jk} \sim N(0, \sigma^2)$ and $U_k \sim (0, \sigma_3^2)$ ((Rodriguez et al. 1995, Goldstein et al. 1996)).

2.3 Result and Discussion

2.3.1 Descriptive Survey Results

The respondent characteristics (Table 2.1) are similar across regions with some exceptions. As expected, South, Southwest, and East regions have higher incomes than other regions. The respondents in those regions and the Northeast region live in more urban environments, while North and Northwest regions were more suburban and rural. The average number of e-bikes per household was relatively stable across regions ranging from 1.22 (Northeast) to 1.63 (East). Notably, most e-bike manufacturing hubs are located in the East region where ownership is highest. Household car ownership ranged from 19-40 per 100 households (Northeast-North, respectively) and motorcycle ownership ranged from 11-47 per 100 households (Northeast-Northwest). The number of licensed drivers in the household was relatively consistent across regions, with the exception of low license rates in Northwest China, which interestingly has very high car and motorcycle ownership rates (both requiring licenses to operate). When asked whether their vehicle reflects their social status, only 4% in Northwest China answered affirmatively for e-bikes, compared to 21% in East China. Central China's respondents viewed status of car ownership strongly (54%) compared to Southwest China's respondents (13%). Finally, next year's car purchase intentions varied dramatically across regions. Southwest China had the lowest intended purchase plans (7.5%), but relatively high car ownership already (38 per 100 households). In contrast, 28.7% of South China respondents intended to buy a car, though they have the same car ownership rate (38 per 100 households) as Southwest China.

Data parameters for the cities surveyed, tabulated across different regions, are shown in Table 2.2. This table reflects the large differences across China's regions.

Table 2.1. Descriptive statistics of sample (N = 947)

Variable	Value	Region							Total Sample
		Center	East	North	Northwest	Northeast	South	Southwest	
Gender	Male	58.8%	51.7%	55.0%	62.2%	56.7%	53.7%	61.2%	54.9%
	Female	41.3%	48.3%	45.0%	37.8%	43.3%	46.3%	38.8%	45.1%
Age	<20	1.2%	1.5%	0.8%	0.0%	0.0%	0.0%	4.4%	1.9%
	20-60	98.8%	96.6%	98.3%	98.6%	98.5%	100.0%	95.6%	96.9%
	>60	0.0%	1.9%	0.8%	1.4%	1.5%	0.0%	0.0%	1.2%
	<20	3.8%	5.0%	11.6%	5.9%	3.1%	11.1%	3.0%	6.0%
Household Income (1,000 Yuan)	20-40	18.8%	12.8%	13.2%	20.6%	26.6%	18.8%	16.7%	15.3%
	40-60	27.5%	19.3%	32.2%	25.0%	29.7%	23.9%	16.7%	22.8%
	60-80	21.3%	19.3%	16.5%	14.7%	15.6%	17.1%	12.1%	17.8%
	80-100	12.5%	15.3%	8.3%	13.2%	12.5%	12.0%	15.2%	14.5%
	100-120	12.5%	13.3%	8.3%	10.3%	7.8%	5.1%	16.7%	11.1%
	120-140	2.5%	6.3%	4.1%	4.4%	0.0%	0.9%	6.1%	4.7%
	>140	1.3%	8.8%	5.8%	5.9%	4.7%	11.1%	13.6%	7.8%
Household Location	Urban	61.3%	67.3%	40.7%	28.8%	81.8%	85.0%	74.6%	64.2%
	Suburb	18.8%	23.2%	16.1%	34.2%	13.6%	8.3%	10.4%	19.3%
	Rural	20.0%	9.4%	43.2%	37.0%	4.5%	6.7%	14.9%	16.5%
Household Composition and Vehicle Ownership	No. of e-bike	1.31	1.63	1.36	1.32	1.22	1.42	1.39	1.47
	No. of car	0.35	0.33	0.40	0.39	0.19	0.38	0.38	0.35
	No. motorcycle	0.31	0.18	0.28	0.47	0.11	0.20	0.17	0.22
	No. of adult	3.00	3.20	3.06	2.96	2.67	2.79	2.98	3.04
	No. of children	0.83	0.81	0.80	0.55	0.60	0.69	0.60	0.74
	No. of Licensed drivers	1.09	1.15	1.25	0.83	1.17	1.28	1.09	1.15
Vehicle Reflects Social Status (%Y)	E-bike	12.5%	21.2%	8.3%	4.1%	10.4%	12.3%	11.8%	15.0%
	Motorcycles	8.3%	19.0%	10.5%	0.0%	0.0%	5.1%	20.0%	7.9%
	Car	54.1%	37.9%	36.4%	38.7%	38.7%	28.6%	12.5%	27.0%
Next Year Car Purchase	(Y=1)	19.0%	20.8%	24.3%	25.4%	14.9%	28.7%	7.5%	21.4%

Note: \$1USD=6.10 Yuan

Table 2.2. Regional description of city-level data where survey respondents were sampled.

Variable	Center	East	North	Northwest	Northeast	South	Southwest
Gender Ratio (male: female)	1.05	1.04	1.04	1.06	1.02	1.08	1.04
Population Density (Person/km²)	491	630	429	264	219	358	306
Household Size	3.25	2.95	3.08	3.42	2.91	3.43	3.06
Private Car Per Capita	0.04	0.06	0.06	0.07	0.04	0.05	0.07
Public Buses per 1000 people (urban area)	0.76	1.07	1.12	1.13	0.89	0.61	1.07
Taxis per 1000 people	0.55	0.78	1.68	0.80	1.32	0.54	0.67
Total Subway Lines	0.3	0.6	1.1	0.0	0.4	0.0	0.5
Total Length of Subway Routes (km)	3.61	22.40	32.57	0.00	10.42	0.00	4.79
GDP per Capita (1000 Yuan)	31.1	44.1	40.7	25.9	28.1	23.1	23.7
Average temperature (°C)	16	16	10	12	6	23	17
Days of the lowest temperature <0°C	49	44	126	123	168	0	6
Days of the highest temperature >30°C	76	78	55	59	25	137	27
Days with Rain	123	145	79	110	145	164	169

Note: City-level data were generated from each city's 2010 Sixth Census Report, 2010 Economic and Social Development Report, 2010 Statistical Yearbook, and the 2010 National Statistical Yearbook of Cities.

The respondents' cities shared some key differences. Population density ranged by a factor of three (219-630 people/km²). The bus transit systems varied from 0.61-1.13 buses per 1,000 people in the urban areas in our dataset. Most of the cities from which respondents are drawn did not have subway service. North and East regions (Beijing and Shanghai) had the most subway service. Average temperature ranged from 6-23°C with Northeast China suffering from the lowest average temperature and the most uncomfortably cold days below 0°C (168 days). In contrast, South China has the warmest average temperature and most uncomfortably hot days exceeding 30°C (137 days). Southwest China has more rainy days (169 days) compared to North China with only 79 rainy days.

These data represent a large amount of geographic variation across China. The differences in respondent characteristics, city-level built-environment and transportation infrastructure, and weather should impact car purchase and ownership choices. Moreover, unobserved regional characteristics could influence vehicle ownership.

2.3.2 Revealed Car Purchase Model 2011-2013

The revealed car purchase model was developed with two possible outcomes, purchasing (1) or not purchasing (0) a car in the two-year time span (Figure 2.6). The author modeled these discrete outcomes on independent variables that included regional-, city- and household-level variables shown in Figure 2.4. The key variables in the model include environmental factors (e.g., temperature and precipitation), socio-demographic factors (e.g., population density), transportation factors (e.g., urban road infrastructure) and policy factors (e.g., e-bike regulations). Household variables include household income and composition variables and vehicle ownership. The vehicle purchase history model tests two alternatives using a three-level hierarchical model. The reference case in this model result is not purchasing a vehicle between 2011 and 2013.

Reported car purchases are tallied for each household for the period 2011-2013. Approximately 18% of the estimation sample reports purchasing a car during the period.

Two variables included in the model contain 35 missing value(s) leaving 911 observations in the estimation sample. The estimated parameters of the model are reported in Table 2.3. Some variables are removed because of very low significance levels, such as car purchase price, the number of children, E-bike standard, etc.

The results are generally intuitive and expected variables are consistent with other studies on motorization, with a few exceptions. The model is statistically significant since Wald Chi-square is 94.56 and the probability of obtaining the Chi-square statistic is less than 0.000. Regarding fixed effects, household income and number of licensed drivers are both positive and significant as expected (p -value = 0.000 and 0.000 separately). The number of cars owned is negative and significant (p -value = 0.000), indicating that the more cars a household owns, the less likely it is to purchase another one. This could also be an indication of parking availability at home, which is often limited or relatively expensive. The number of motorcycles owned is insignificant factor, possibly because more than 200 cities in China have heavy motorcycle restrictions. and e-bikes and cars can be suitable substitutes for motorcycles (Yang 2010). The number of e-bikes owned is an insignificant factor to car ownership 2011-2013. Duration time since first motorized vehicle (e-bike/ motorcycle/ car) purchase is positive and marginally significant (p -value = 0.069). The negative and significant constant term suggests that, accounting for the other variables in the model, there is a tendency for households not to purchase a car during the period.

Regional- and city- level variation in socio-economic factors, built- environment, transit density and weather patterns have little influence overall on car purchase probability after controlling for household-level characteristics. However, there are a couple of exceptions. City-level GDP per capita is positive and significant (p -value = 0.050), consistent with most other motorization findings. Given that household income is controlled for in the estimation, it may be the case that per capita GDP is capturing a peer effect. For example, households in higher income areas are more likely to have neighbors that own cars, and this might place pressure on a household to purchase a car. Taxi

density is negative and significant (p -value = 0.015), suggesting that a household in a city with high taxi availability is less likely to purchase car. This could be an indication that taxi availability and personal car ownership are perceived as substitutes. The East China region is weakly significant and negative relative to the omitted Center China region (p -value = 0.081). For random effects, Table 2.3 shows the estimated standard deviation components, indicating small random effects at the regional- and city- levels.

2.3.3 *Intended Car Purchase Model 2013-2014*

Car purchases plans are determined based on the answer to a ‘yes/no’ question about whether the household plans to purchase a car within the next year. Approximately 21% of the households in the estimation sample state that they plan on purchasing a car within the next year. Some missing values left 902 observations in the estimation sample. The car purchase plan model estimates are presented in Table 2.4. The Wald Chi-square of 69.10 with a p -value of 0.000 shows that the model as a whole fits significantly.

Regarding to the fixed effects, household income and number of licensed drivers are strong positive determinants (p -value = 0.008 and 0.000 separately) as expected. Number of cars owned is strong and negative (p -value = 0.000) showing that the more number of cars owned, the lower probability to purchase another car. The number of e-bikes owned is highly significant and positive (p -value = 0.001). This is a potential indication that e-bikes are not perceived as substitutes for cars, and that e-bikes may be a key vehicle in the motorization pathway toward car ownership. Also, some cities have begun to restrict the use of e-bikes in urban core areas, which could encourage car purchase intention, though the author does not control for those policies. However, the number of e-bikes is an insignificant factor in the revealed model 2011-2013. The result could show that, as car purchase intentions increase over time, people with e-bikes ownership becomes more important in the decision process. The number of motorcycles owned is insignificant, similar to the previous model. Considering the decrease in motorcycle sales and the increase in e-bike sales in China, many consumers who had originally intended to buy motorcycles may have chosen to buy e-bikes.

Table 2.3. Estimates of revealed car purchase model 2011-2013

Indicators			Coefficient	Std.Err.	Z-value	P-value
Fixed-effects						
Constant			-3.769***	0.553	-6.82	0.000
Level-1 Correlates	Household income (1000 Yuan)		0.172 ***	0.031	5.54	0.000
	No. of E-bikes (2011)		0.072	0.145	0.50	0.616
	No. of Cars (2011)		-2. 889***	0.500	-5.83	0.000
	No. of Motorcycles (2011)		-0.135	0.286	-0.47	0.638
	No. of Licensed Drivers		0.515***	0.101	5.09	0.000
	Duration Time of First Motorized Vehicle Ownership (years)		0.0861*	0.045	1.82	0.069
Level-2 Correlates	GDP per Capita (1000 Yuan)		2.23E-05**	0.000	1.95	0.050
	Urbanization (urban residents per metropolitan area residents)		1.239	1.000	1.24	0.216
	Road density (km ² of road per urban resident)		-0.035	0.034	-1.07	0.223
	Bus density (urban buses per 10,000 urban residents)		0.038	0.028	1.35	0.176
	Taxi density (urban taxis per 10,000 urban residents)		-0.080**	0.033	-2.44	0.015
	Days with temp <0 oC (highest temperature <0°C, 2010)		0.007**	0.007	1.01	0.031
Level-3 Correlates	Region Indicator	Center of China	Base			
		East of China	-1.1315*	0.391	-2.90	0.004
		North of China	-0.287	0.548	-0.52	0.600
		Northeast of China	-0.553	0.886	-0.62	0.533
		Northwest of China	-0.732	0.677	-1.08	0.280
		South of China	-0.414	0.476	-0.87	0.384
		Southwest of China	-0.198	0.539	-0.37	0.714
Random-effects						
Region ID: Identity			9.027E-13	0.108	-	
Std deviation of region constant						
City ID: Identity			5.10E-012	0.254	-	
Std deviation of city constant						
Goodness of Fit						
Log Likelihood			-285.767			
Wald Chi-square			94.56			
Prob. > Chi-square			0.000			
Sample Size			911			

Note: ***, **, *, * denote estimate is statistically significant at the 1, 5, and 10% levels, respectively.

The duration since a household first purchased a motorized vehicle (e-bike/motorcycle/car) is significant and positive (p-value = 0.033). It is not clear whether this is an indication that long-time vehicle owners ultimately move up a motorization pathway toward car ownership, or simply a proxy for age of the household vehicle fleet, and hence the need for replacement. Considering the low car ownership of China compare to Western countries, it may indicate that e-bikes and motorcycles will not be the terminal of the motorized pathway.

Similar to the car ownership model (Table 2.3), few variables are significant at the regional- and city-levels. Northwest China has a significant and positive influence (p-value = 0.017) on intention to purchase a car relative to the reference Central China region. South of China has is a positive and weakly significant influence on intention to purchase a car compared to the reference Central China. Population density is positive and weakly significant (p-value = 0.109). However, urbanization rate (ratio of urban to metropolitan population) is very marginally significant and negative (p-value = 0.115) showing that citizens of higher urbanized areas tend not to purchase a car. Bus density (urban buses per 10,000 urban residents) has negative influence on car purchase intention. In general, high urbanized areas have high public transit systems and tightened car purchase policies which would discourage people's car purchase intention. The number of days that highest temperature below 0°C is positive and weakly significant (p-value = 0.148) indicating the respondents from colder areas tend to purchase cars. It indicates that people consider cold days more than other weather conditions. Considering the random effects, the standard deviation of the intercept of region indicator is relatively small. However, the standard deviation of the city-level intercept larger, indicating that car purchase fixed effects vary across cities.

Table 2.4. Estimates of intended next-year car purchase model 2013-2014

Indicators		Coefficient	Std. Err.	Z-value	P-value	
Fixed-effects						
	Constant	-2.889****	0.501	-5.75	0.000	
Level-1 Correlates	Household income (1000 Yuan)	0.069****	0.026	2.65	0.008	
	Household size	0.100**	0.060	1.66	0.096	
	No. of E-bikes (2013)	0.362****	0.107	3.38	0.001	
	No. of Cars (2013)	-0.979****	0.229	-4.28	0.000	
	No. of Motorcycles (2013)	-0.187	0.228	-0.83	0.409	
	No. of Licensed Drivers	0.368****	0.0924	3.97	0.000	
	Duration Time of First Motorized Vehicle Ownership (years)	0.068***	0.032	2.14	0.033	
Level-2 Correlates	Population density (city residents per km ²)	0.001*	0.000	1.20	0.109	
	GDP per Capita (1000 Yuan)	-8.80E-06	0.000	1.01	0.314	
	Urbanization (urban residents per metropolitan area residents)	-1.43*	0.915	-1.57	0.115	
	Subway density (km of subway per 10,000 urban residents)	-2.16	2.78	-0.78	0.430	
	Bus density (urban buses per 10,000 urban residents)	-0.063***	0.025	-2.53	0.012	
	Taxi density (urban taxis per 10,000 urban residents)	0.030	0.031	0.99	0.300	
	Days with temp <0°C (highest temperature <0°C, 2010)	0.010*	0.007	1.40	0.148	
Level-3 Correlates	Region Indicator	Center of China	Base			
		East of China	-0.05	0.330	-0.15	0.878
		North of China	0.274	0.423	0.65	0.517
		Northeast of China	-0.169	0.531	-0.32	0.750
		Northwest of China	1.162***	0.487	2.39	0.017
		South of China	0.642*	0.402	1.60	0.110
		Southwest of China	-0.579	0.624	-0.93	0.353
Random-effects						
Region ID: Identity	Std deviation of region constant	1.01E-08	0.100	-		
City ID: Identity	Std deviation of city constant	0.062	0.843	-		
Goodness of Fit						
Log Likelihood		-411.54564				
Wald Chi-square		69.10				
Prob. > Chi-square		0.000				
Sample size		902				

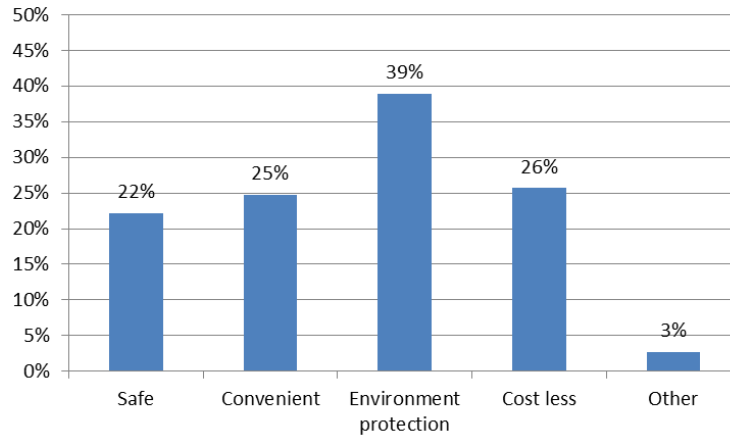
Note: ****, ***, **, * denote estimate is statistically significant from zero at the 1, 5, 10, and 15% levels, respectively.

2.3.4 New Energy Vehicles

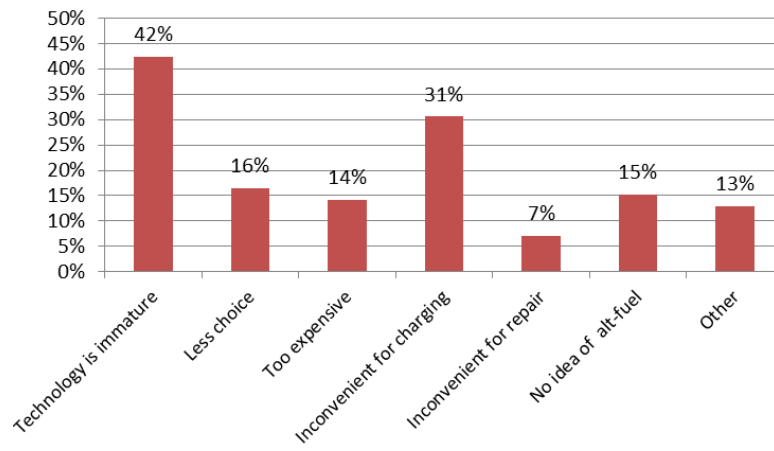
One exploratory question was asked related the consideration of an alternative fuel vehicle. China's "New Energy Vehicle" initiative has promoted alternative fuel vehicles, including battery electric, plug-in hybrid and hydrogen fuel cell vehicles as desirable vehicles in the future. It is unclear how knowledgeable consumers are with the relative performance or price of these vehicles or if they can accurately make a purchase decision outside of a careful stated preference experiment. Still, a follow-up question to those who said they intend to buy a car in the next year was the consideration of a "New Energy Vehicle" and reasons why they would or would not consider that type of vehicles. This can, at least, provide some initial impressions of these types of vehicles. Of the 198 respondents who said they intend to buy a new car, 57% said they would consider an alternative fuel vehicle. The most highly rated reason for choosing an alternative fuel was for altruistic environmental protection. However, another highly rated reason was related to low cost (including purchase cost, operation cost and maintenance cost.), indicating that survey respondents are responding to educational initiatives, are aware of government subsidies, or are familiar with the relatively lower operating costs of electric vehicles through the use of their e-bikes. Safety (perceived occupant protection) and convenience (easy to drive and maintain) were also highly rated. The most highly rated reasons respondents would *not* consider alternative fuel vehicles is because of immature technology and inconvenient charging/fueling options (Figure 2.8) which is also pointed out by a recent study by Wan et al. (2015). While these results are not conclusive, they lend some insight into opportunities or barriers for alternative fuel vehicle adoption.

2.4 Conclusion

This study targeted existing e-bike owners and investigated their future car purchase plans with the goal of identifying geographic, built-environment, socio-economic, transportation and environmental variables that influence car purchase decisions, in the past and future.



(a)



(b)

Figure 2.8. Reasons for considering an alternative fuel vehicle (a) and reasons for not considering an alternative fuel vehicle (b).

This paper adds to the growing body of literature investigating motorization, focusing on household- and city-level factors, rather than national trend analysis. The author found that household variables dominate the models, with few exogenous variables significantly influencing purchase decisions. Car ownership decreased the chances of purchasing a car. Duration time from first motorized vehicle purchased increase the chances of purchasing a car. Household income and number of licensed drivers increase the chances of purchasing a car. High e-bike ownership increased the chances of purchasing a car which indicates that e-bikes may not be the terminal or substitutes for cars of the motorized pathway.

There were a few regional differences as well, with weaker demand in Northeast China. Northwest China and South China have relative stronger car purchase intentions. High taxi density, bus density, population density, and urbanization reduced the likelihood of purchasing a car, meaning advanced public transit could be temper car ownership. Also, advanced public transit usually is built in the bigger cities that may often have more strict regulations or economic barriers to control car ownership. Of the environmental variables, only the number of cold days had significant effect on car purchase decisions. More restrictive e-bike policies did not influence car purchase. This could be because restrictive e-bike policies might not be strictly enforced; and cities with restrictive e-bike policies tend to have high taxi and bus density, which counters the influence of policy on car intention.

Many of these relationships corroborate other studies. However, many of the models' insignificant variables are also important. This analysis builds on other studies and contributes to the evolving understanding of how China motorizes, particularly among a large subset of transportation users, existing owners of e-bikes. Findings in this study can assist policy makers in identifying factors that are within their control (e.g., transit service) and factors that are beyond their control (e.g., geography) when developing approaches to control motorization.

There are four main limitations to this study. First, the limited sample (based on available sampling data ability) of only e-bike owners does not allow us to estimate the true effect of e-bike ownership on vehicle purchase behavior, i.e., the author cannot compare to non-e-bike owners. Nonetheless, the author modeled motorization within a subset of total transportation system users; an important subset on the verge of adopting fully motorized vehicles. Secondly, since this survey was a telephone survey across China, our sample was limited to the dataset spanning 2008-2012 to assure reliable contact information (the author attempted to contact e-bike consumers from before 2008, most of the phone numbers were disconnected). Thirdly, more data should be collected in the future to improve the models' accuracy. The small sample size limits the power of the models. Last, the author did not consider car ownership cost in this study as an explicit variable, which certainly has a significant influence on car ownership model. Controlling for variable car ownership costs across the sample is an area of future improvement to the model.

CHAPTER 3
MAKING THE SHIFT: ATTRACTING CONVENTIONAL DRIVERS
TO ELECTRIC VEHICLES IN CHINA'S DEVELOPING CAR
MARKET

Abstract

As the Chinese economy rises along with its middle class, the trend toward driving has been rapid and unstoppable. Shifting more potential conventional vehicle (CV) users to electric vehicles (EVs) is an efficient and effective way to reduce China's challenges with regard to energy, air pollution, and greenhouse gas (GHG) emissions. Though current policies have covered many areas for promoting electric vehicles, electric-car drivership is still in the very early phase, with low market shares. It is not yet clear how the Chinese public perceives electric vehicles or what kinds of factors will encourage potential vehicle customers inclining to electric vehicles. This study examines the household vehicle purchase decisions of a 1,216-person sample in Beijing, China using the intercept survey method. From the survey responses, the author found that statistical differences exist between future electric vehicle buyers, future CV buyers, and people who have no purchase plan with regard to their experience with electric vehicles, general rating of electric vehicles, and social status concerning CVs and EVs. Two choice models were developed. The first was to estimate the subjects' intention to buy a car in the near future, and the other was to assess attributes that contribute to choosing CV cars, plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs). The results show that the chances of purchasing either PHEVs or BEVs increased with gender (male) and high household income. People's pre-existing inclination to choose a CV decreased their chances of purchasing EVs. Chances of buying PHEVs declined among people who planned to have a driver license in 3 years or a longer duration of first motorized vehicle ownership. The subjects' household number of electric bicycles increased their chances of purchasing PHEVs. In addition, people who had driven or ridden in an EV previous to the study had a greater chance of buying a BEV, but people who already had a driver's license and high purchase budget had lesser chances of purchasing a BEV. Policy recommendation based on customers' perspectives are offered based on the results, including direct monetary benefits to driving EVs, daily use benefits, effective advertising and promotion policies, impact on middle- and low-income markets and part

of the top-end market, social status influence, the development of well configured micro EVs, and test-driving and free-driving activities.

3.1 Introduction

Since 2003, more than 150 million passenger cars have been sold in China's domestic market (National Bureau of Statistics 2012b, China Association of Automobile Manufacturers 2014b, China Association of Automobile Manufacturers 2015, Ling et al. 2015, Statista 2017). By 2050, the total vehicle stock could be as large as 530 to 623 million (Huo et al. 2012a). Ou et al. (2010a) predict that these vehicles will consume up to 564 million tons of oil equivalent and will emit up to 1,636 metric tons of CO₂ per year. In 2012, China became the world's largest emission producer (Marquis et al. 2013). Already, most Chinese cities were facing severe environmental and climate challenges accompanied by the country's considerable economic growth and the dramatic expansion of its transportation systems. In June 2015, China set a target to lower the carbon intensity of its GDP by 60 to 65% by 2030 from its 2005 values (Climate Action Tracker 2015). A promising means to solve a series of energy and environmental issues appears to be the advent of electric vehicles. The Chinese government aims to curb GHG emission in the road transportation sector by promoting new energy vehicles¹ (NEVs) and regulating vehicle fuel economy (Ou et al. 2010c, Zhang et al. 2011).

From 2010 to 2016, 0.95 million NEVs were sold in China as shown in Figure 3.1 (China Association of Automobile Manufacturers 2014b, New Energy Vehicle Association 2014, Association of Beijing New Energy Automotives 2015, China Auto Association 2017, Ou et al. 2017). Although NEVs sales are increasing rapidly, the NEV market share was only 2.1% of the 24.4 million passenger cars sold in the domestic market in 2016. A large gap still exists between current NEV sales and the expected goal (Zhang et al.

¹ New energy vehicles (NEVs) are generally defined as all types of cars that consume, fully or in part, alternative fuels like ethanol, and electricity (Jansson 2011). In this paper, "electric vehicle" (EV) includes battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV) (Ou et al. 2017).

2014). Understanding potential consumers' attitude and perspective towards NEVs (mainly EVs) is important because it not only will support the decisions made by the government and private sectors, but also contributes to decision-makers' overall understanding of market demand. Unlike Western countries with mature fleets, which are making efforts to switch current conventional car (CV) users to cleaner vehicle users, China is still in the early stages of motorization. Shifting prospective CV buyers to electric vehicle buyers could be an effective way to reduce challenges that face the country in the areas of energy, air pollution, and greenhouse gas emissions. Furthermore, as a country with a large percentage of e-bike users (over 250 million e-bikes have been sold since 1998 (Ling et al. 2015)), few studies have explored e-bike user experiences and their influence on the purchase of EVs, which have similar barriers (i.e., range anxiety, charging).

This paper aims to answer the following questions: 1) How well do potential customers understand and how familiar are they with EVs? 2) How do respondents make purchase decisions among CVs, PHEVs, and BEVs? 3) Does e-bike use experience have any influence (encouraging or discouraging) on EV purchase decisions? This paper begins to fill an important gap by investigating purchase intention from customers' points of view and making policy recommendations based on the results.

Focusing on how potential customers perceive BEVs and PHEVs and make purchase decisions, the author surveyed 1,216 respondents in Beijing, China. The author constructed two models: one to assess factors influencing all respondents' intentions to purchase a car in the near future (which is an extension of a 2015 study focusing on e-bike owners' car purchase intentions in 2013 (Ling et al. 2015)). The other model assesses factors influencing consumers' choices among CVs, PHEVs, and BEVs. While previous studies have focused on purchasing one type of vehicle, omitting the experiences of China's cities, where 150 million e-bikes on the roads make China's new energy vehicle environment unique, this paper contributes important insights into vehicle choice behavior regarding CVs, PHEVs, and BEVs as well as controlling for e-bike

influence. The remainder of the paper is organized as follows: the Background section discusses government policies with regard to EVs as well as previous studies on NEV purchase attitudes and factors influencing purchase intention. The Methods and Data section discusses the methodology and data collection used in the study. The Result, Analysis, and Discussion section presents results and discussion on NEV purchase and policy implications. Finally, conclusions and limitations are presented in the Conclusions section.

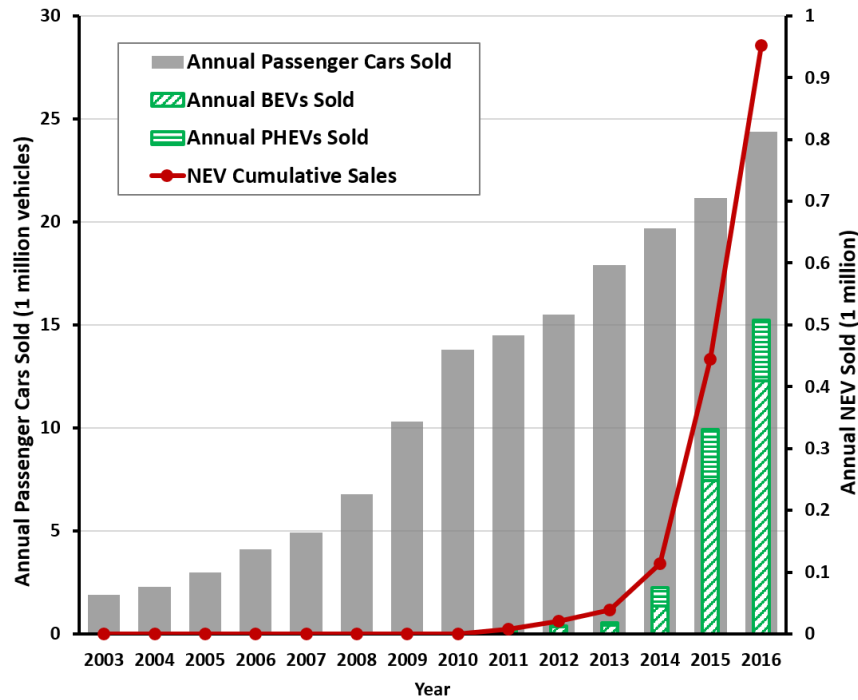


Figure 3.1. Conventional vehicles and NEVs sold since 2003

3.2 Background

3.2.1 Government policy

Since the turn of the 21st century, the Chinese government has launched comprehensive policies and incentives to promote development of the NEV sector and NEV market penetration (Marquis et al. 2013, Hao et al. 2014). All NEV-related policies can be classified into the following seven categories, summarized in Figure 3.2: macroscopic

policies, demonstration policies, subsidization policies, preferential tax policies, technical support policies, industry management policies, and infrastructure policies (Gong et al. 2013, China Automotive Technology and Research Center 2015, Li et al. 2016).^{2, 3} Key policies related to NEVs are listed in accordance with the Chinese government's "Five-Year Plan" with details below the horizontal axis.

In the 10th Five-Year Plan (2001-2005), the Ministry of Science and Technology of the Chinese government established an EV key project in the National High-tech Development Plan (known as the 863 Program) (Gong et al. 2013). Then in 2004, the National Development and Reform Commission of the Chinese government developed an Energy Savings Medium- and Long-Term Plan and identified the auto industry as one of the pillar industries (National Development and Reform Commission 2004a, National Development and Reform Commission 2004b). In the 11th Five Year Plan (2006-2010), research activities focused on the establishment of "Three Platforms" to promote the development of the NEV industry (Ministry of Science and Technology 2006). In the Electric Vehicle Subsidy Scheme launched in 2009, followed by an update in 2013, the details of a scheme to subsidize the purchase of EVs were specified, including the subsidy's duration, scope, standards, and phase-out mechanism. In 2009, four Chinese government ministries initiated the "Ten Cities, Thousand Vehicles" program and by 2011, the number of pilot cities had climbed to 25 (Marquis et al. 2013). By June 2012, critical government targets were projected in the "Energy Saving and New Energy Vehicle Industry Development Plan (2012-2020)," which aimed for cumulative sales of BEVs and PHEVs to reach 0.5 million by 2015 and 5 million by 2020 (Marquis et al. 2013). To prompt growth, the vehicle sales tax and vessel tax would be exempted or reduced for CVs (Ministry of Finance 2014, Ministry of Finance 2015). China's 13th

² The "Three Transverses" refers to the three types of NEVs, which are hybrid electric vehicles, pure electric vehicles, and fuel cell electric vehicles. The "Three Longitudes" refers to the three NEV-related technologies, such as drive motor, and power battery.

³ The "Three Platforms" refers to technological platforms, research and development platforms, and product platforms.

Five-Year Plan (2016-2020) states that the Chinese government will promote the use of new energy vehicles and improve the industrialization level of electric cars (China Daily 2015). Part of this effort includes building infrastructure to charge EVs. Charging infrastructure is under construction and aims to provide at least 12,000 charging stations and 480,000 individual bollards by 2020 (National Development and Reform Commission 2015, State Council 2015, Li et al. 2016). In January 2016, China set the price floor of domestic gasoline prices as long as crude oil is below 40 dollars per barrel citing environmental concerns and rapidly increasing conventional vehicle ownership, according to the top price regulator, the National Development and Reform Commission (NDRC). NDRC believes that a low gasoline price would be detrimental to air quality and slow the shift toward greater use of NEVs (Zheng 2016).

Under these policies and statements, EV pilot studies have been conducted in different cities. According to different local governments' strengths and geographic and social conditions, the pilot cities were able to set their own vehicle rollout strategies by following the basic guidelines ordered by the central government.

Marquis et al. (2013) discussed five representative cities including Beijing, Shanghai, Shenzhen, Hangzhou, and Chongqing. Beijing is strongly motivated to develop an environmentally friendly city image. The city government focused on preferential policies and public sector support of EVs. Shanghai focused on creating an EV international demonstration zone in the Jading district, and tried to spread EV rental businesses across the city. Shenzhen focused on creating a leasing model to reduce the cost of purchasing EVs. Hangzhou was the first city in China to launch a program allowing people to rent cars and batteries separately, while Chongqing was the only pilot city launching grid-intensive fast-charging EV technology.

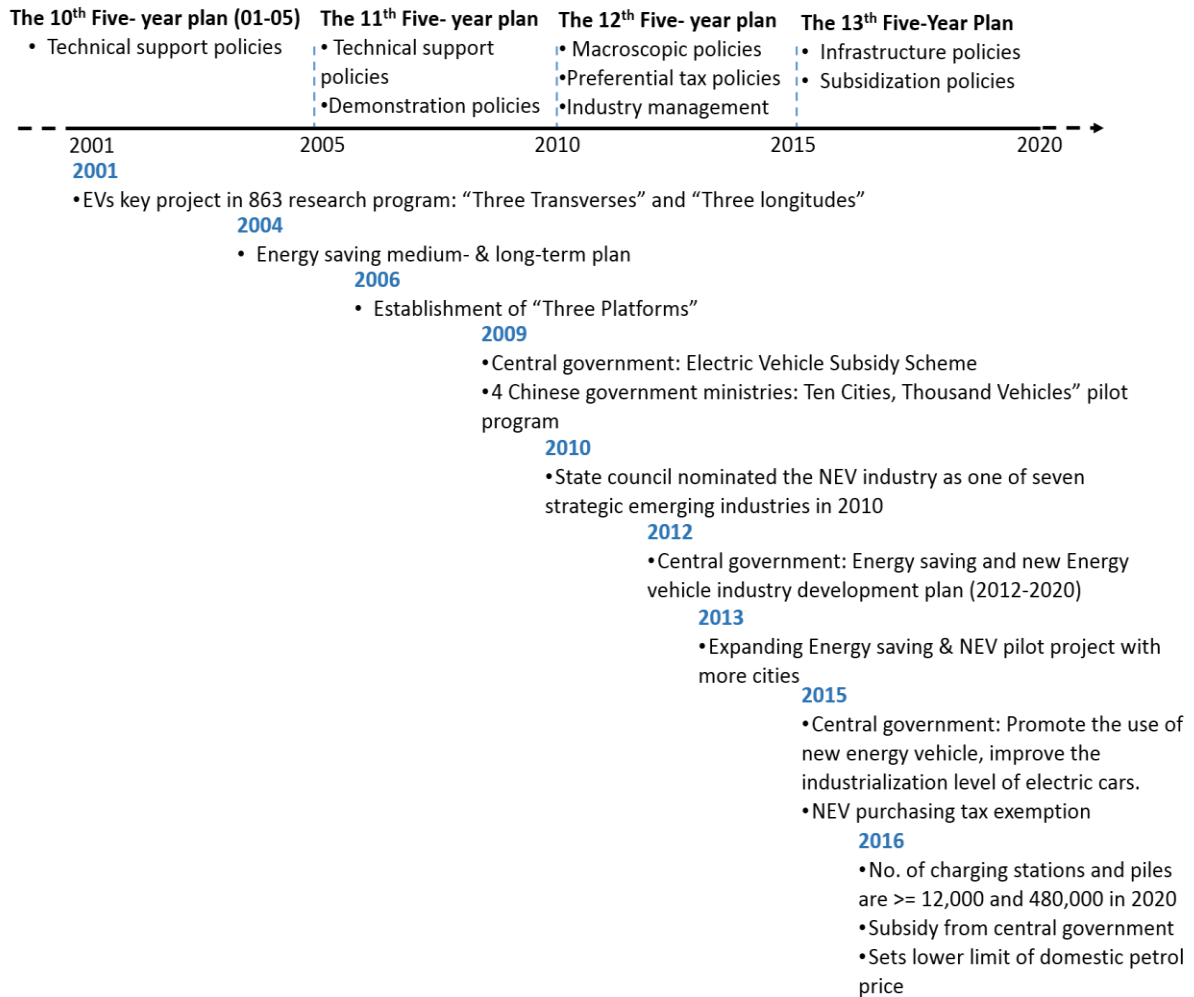


Figure 3.2. Major Chinese Government NEV Policies Since 2001 (extended from Gong et al. (2013))

3.2.2 Literature review

The growing literature on consumer EV adoption focuses on the different adoption behaviors of consumers toward EVs using differing theories and methodologies. Five theoretical frameworks regarding EV adoption have been identified: the framework of planned behavior and rational choice theory; a framework using normative theories and environmental attitudes; a framework emphasizing the role of symbols, self-identity and lifestyle; a framework considering the diffusion of innovation and consumer innovations; and a framework dealing with consumers' emotions (Rezvani et al. 2015, Adnan et al. 2017). Since EVs currently have a low market share, studies of their adoption mainly focus on purchase intention (Rezvani et al. 2015).

3.2.2.1 New energy vehicle attitude and purchase intention studies

In spite of the well-known environmental benefits of electric vehicles, the number of EVs in use is still small. Electric mobility is still in the early phase, with low market shares. Previous studies have found that consumers' perceptions and acceptance of EVs, in addition to other factors, affect their purchase decisions. Representative studies of EV adoption intention from consumers' point of view in various countries are summarized in Table 3.1 (Zhang et al. 2011, Rezvani et al. 2015), which shows data for the studies' samples, EV types, data collection, methodologies, the aims of the studies, and factors including demographic characteristic; perception and social factors; technological factors; policy related factors; and environmental influence. Most of these studies explore barriers or factors influencing consumers' purchase intentions toward alternative fuel vehicles in developed countries and regions. The table further reveals that stated preference (SP) survey methods are widely used to collect data. EV types mentioned in the studies vary but include alternative liquid-fuel vehicles, hydrogen fuel cell vehicles, battery electric vehicles, and plug-in hybrid electric vehicles. While a good number of studies have been done on EVs in Western countries, little is known about perception and awareness of EVs in China, which, as noted earlier, is context-dependent (Rezvani et al. 2015). Furthermore, while previous studies explored customers' purchase intentions towards a .

Table 3.1. Summary of key studies of NEV perceptions and purchase intentions

Authors (year)	EV	Sample; Data source; Methodology	The aim of the paper	Factors ¹				
				Dg	PS	TP	PF	En
Brownstone et al. (2000)	AFV ²	4,747 household, U.S.; Telephone interview; Multinomial and mixed logit models	To compare models' performance on AFV preference	√		√		√
Dagsvik et al. (2002)	AFV ³	642, Norway; Stated Preference (SP) survey; Random utility models	To analyze the potential demand for alternative fuel vehicles	√		√		
Lane et al. (2007)	Low carbon ⁴	UK; Interviews & questionnaires; Qualitative analysis	To find attitudinal barriers inhibiting the adoption of cleaner vehicles in the UK		√	√	√	√
Erdem et al. (2010)	HEV	1,974, Turkey; A web-based SP survey; Ordered probit model	To determine the factors impact on consumers' willingness-to-pay for hybrid vehicle in Turkey	√	√	√		√
Zhang et al. (2011)	EV ⁵	299 trainees in driving school, China; SP survey with questionnaires; Binary logit model	To examine the factors that affect EV purchase time, and purchase price	√		√	√	
Lieven et al. (2011)	EV ⁵	1,152, Germany; A web-based survey; Rational choice theory	To identify barriers to consumers' intention to buy		√	√		√
Zhang et al. (2013)	NEV ⁶	349 potential consumers from auto dealers, China; SP survey; Regression model	To identify purchase motivation and examine the impact of government policies	√	√	√	√	√
Schuitema et al. (2013)	EV ⁵	2,728 respondents who had purchased a new or nearly new car in last 5 years, UK; A web-based SP survey; Multiple mediation model	To understand how private car drivers' perceptions of vehicle attributes may affect their intention to adopt EVs		√			
Burgess et al. (2013)	BEV	55 private drivers, UK; Interviews after 3 months of trial; Qualitative analysis	To reveal symbolic meanings of EVs and personal resistance		√	√		
Krupa et al. (2014)	PHEV	911 residents, USA; A web-based SP survey; Ordered logit regression	To better understand factors influencing the potential for PHEV market penetration		√	√		√

Table 3.1.Continued.

Authors (year)	EV	Sample; Data source; Methodology	The aim of the paper	Factors ¹				
				Dg	PS	TP	PF	En
Larson et al. (2014)	BEV, PHEV	240 experienced drivers, students, and others, Canada; SP survey; Price assessment method	To evaluate pricing and identify appropriate policy response	√	√	√		
Peters et al. (2014)	EV ⁵	969 respondents, Germany; A web-based SP survey; Regression model	To discuss relevant factors in the acceptance and adoption of EVs		√	√		
Sang et al. (2015)	EV ⁵	751 private vehicle drivers, Malaysia; A web-based SP survey; TPB, regression model	To highlight major predictors that will affect public acceptance towards EV usage intention					
Li et al. (2016)	NEV ⁶	727 consumers from auto dealers, China; SP survey; Four paradigm model	To analyze consumers' evaluation of government policies				√	
Wang et al. (2016)	HEV	433 consumers from auto dealers, China; SP survey; TPB, structure equation model	To investigate consumers' intention to adopt HEVs	√	√			√
Li et al. (2017)	BEV	940 consumers from auto dealers, China; SP survey; TPB, structure equation model	To investigate household factors in BEV adoption	√	√			

NOTE:

1. Dg. = demographics and household characteristic; P.S. = psychological and social status needs; Te. = technological factors and performance; Po. = government policies and financial benefit; En. = environmental concerns. √ = included in paper; blank cell = not included in the paper.
2. In Brownstone et al. (2000), alternative fuel vehicles (AFVs) include electric, methanol, and compressed natural gas vehicles.
3. In Dagsvik et al. (2002), alternative fuel vehicles (AFVs) include electric powered, liquid propane gas powered, and hybrid electric vehicles.
4. In Lane et al. (2007) paper, “low carbon car” defined as emitting $\leq 100\text{g CO}_2$ per km. To the paper’s date, “low carbon car” included several brands’ gasoline hybrid and battery electric cars.
5. Electric vehicle (EV) is used in the paper without specific explanation of EV types. All the following EVs in this table refer to the general idea of electric vehicles.
6. New energy vehicle (NEV) without explanation or definition.

wide range of NEVs, or focused on one type of electric vehicles, little is known about customers' more specific purchase inclinations towards BEVs and PHEVs, which are the two mainstream EVs in the market.

Five main studies have focused on the alternative fuel vehicle market in China. A study conducted in Nanjing, China surveyed 299 highly educated, high-income people in a driving school to determine their acceptance of EVs, their anticipated purchase time and anticipated purchase price (Zhang et al. 2011). They found that, as EV technology improves, the market expands, and the government's policy and subsidy support continue, EVs could be popular among a broad population of people who intend to buy a car. Another study surveyed 349 potential consumers from automobile dealers from 13 cities in China to examine the impact of government policies (Zhang et al. 2013). In a similar study, household factors and government policy's influence on EV purchase were studied using empirical data from visitors to automobile dealers in China (Li et al. 2016, Wang et al. 2016, Li et al. 2017). However, consumers who were contacted in automobile dealerships (Automobile 4S stores⁴) usually had pre-existing brand or model inclination as most 4S stores provide single-brand businesses, limiting customer exposure to a narrower range of EVs

3.2.2.2 Factors influencing new energy vehicle purchase

As mentioned in the previous section, many studies have been devoted to discussing various factors in EV purchase intention. According to previous studies, these possible factors can be classified into five categories: demographic and household characteristics, perception and social status, technological factors and performance, government policy and financial benefit, and environmental concerns.

⁴ 4S refers to sale, spare part, service, and survey (information feedback). Auto 4S stores have two basic models. One is horizontal development which is a multi-brand business model. The other is vertical development which is a single-brand business model that can be commonly seen in China.

Factors influencing new energy vehicle purchase include several aspects: household characteristics, performance, financial benefits, environment concerns, moderating effects of government policies, and psychological and social status needs, as shown in Figure 3.3 (Brownstone et al. 2000, Hidrue et al. 2011, Jansson 2011, Lieven et al. 2011, Zhang et al. 2011, Delang et al. 2012, Bessenbach et al. 2013, Jones et al. 2013, Rezvani et al. 2015, Wang et al. 2016) .

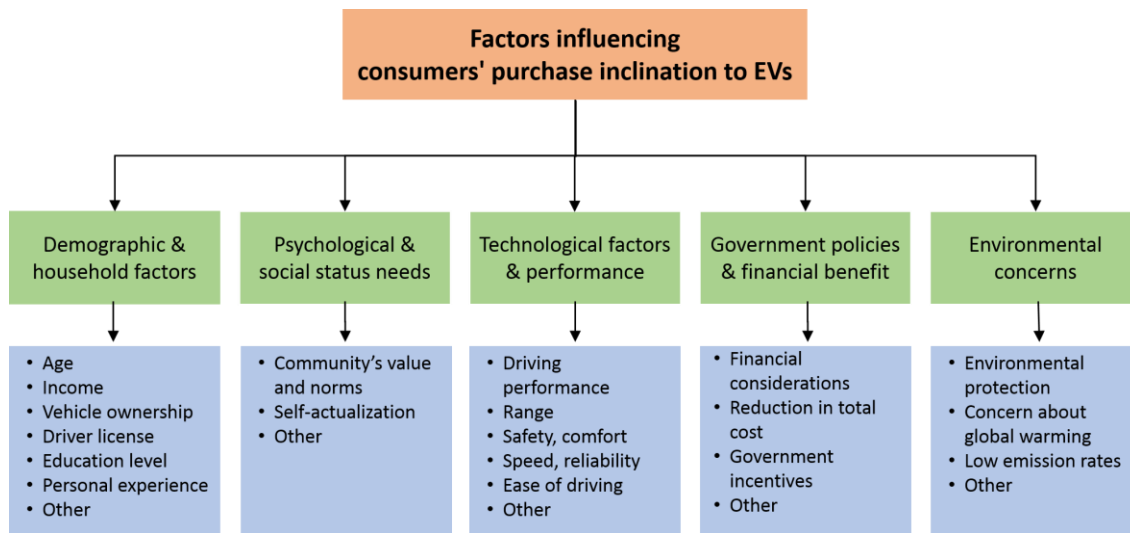


Figure 3.3. Factors influencing consumers' perception to EVs

Previous studies have shown that consumers' impressions of NEV performance plays an important role in the purchase decision-making process (Lieven et al. 2011, Schuitema et al. 2013, Zhang et al. 2013, Rezvani et al. 2015). Some researchers found that performance considerations, such as comfort, noise, ease of driving, and automatic transmission were the most important factors affecting consumers' adoption of PHEVs, based on a UK survey of 1,263 respondents (Ozaki et al. 2011). According to another study conducted in the UK, vehicle performance and mile range were important attributes largely because they are related to other attributes derived from owning and using EVs

(Schuitema et al. 2013). The result is consistent with a study in China which showed that a high degree of safety, high quality, and good performance are key factors in the acceptance of EVs (Zhang et al. 2011). People who believe that pro-environmental self-identification corresponds to their self-image are more inclined to have a positive perception of EVs, according to a nationwide online survey of potential EV adopters in the UK (Schuitema et al. 2013). Empirical research on EV acceptance reveals that consumers are concerned with financial benefit and think that EVs could reduce maintenance costs and improve fuel-efficiency, while some researchers found that the purchase price of EVs is the greatest determinant of EV purchase intention (Lane et al. 2007, Potoglou et al. 2007, Zhang et al. 2013). Also, some people may use environmental protection actions like driving an EV to express their commitment to reducing their ecological footprint (Erdem et al. 2010). Fewer studies have addressed customers' attitudes and purchase intentions toward EVs in China. More particularly, few studies have explored consumers' experience with e-bikes as an influencer of electric car attitudes. This study draws from the body of literature and applies those findings to investigate factors influencing Chinese households' perception and adoption of NEVs, focusing on the purchase decision.

3.3 Methods and Data

3.3.1 Data collection

In July 2015, an intercept survey was conducted in the five main urban districts of Beijing, including Dongcheng district, Xicheng district, Chaoyang district, Haidian District, and Fengtai district. Although Beijing consists of 16 districts (Beijing Municipal Bureau of Statistics 2010), about 60% of the city's residents live in those five districts. The survey contained two parts. The first part included respondents' general understanding and attitudes toward electric vehicles, conventional vehicles, and e-bikes. The second part asked respondents about their demographics, their household vehicle ownership, their planned vehicle purchase decisions, and their household vehicle purchase history. To measure respondents' familiarity with EVs, respondents were asked

to describe their understanding and knowledge of EVs. Then the trained surveyors rated respondents' familiarity level with EVs as “unfamiliar” (1), “somewhat familiar” (2), and “familiar” (3). Respondents were surveyed at different locations in the districts, including malls, supermarkets, subway and bus stations, and entertainment venues to get a wide range of sample population. An intercept sampling approach was used to randomly approach adults at each location as they passed an arbitrary point. Data were collected in each district between 9:00 am and 6:00 pm on multiple weekdays and weekend days. A pilot survey revealed limitations, particularly in the public understanding of questions related to social status attributes. Also, because people have different opinions of EVs, since there are many different types of electric vehicles, such as electric buses and lightweight electric vehicles, surveyors were trained to explain these concepts carefully and a picture of a conventional electric car was provided to help them explain.

After the removal of samples lacking important information, such as household income and household vehicle ownership, 1,216 surveys were analyzed. The total rejection rate was 46%, with 43% male rejection rate. Cronbach's alpha was used to assess the internal consistency of the Likert-scale questions (Cronbach 1951) and was computed by correlating the score for each scale item with the total score for each observation and comparing that to the variance for all individual item scores:

$$\alpha = \left(\frac{k}{k-1}\right)\left(1 - \frac{\sum_{i=1}^k \sigma_{y_i}^2}{\sigma_x^2}\right)$$

where k refers to the number of scale items, $\sigma_{y_i}^2$ refers to the variance associated with item i , and σ_x^2 refers to the variance associated with the observed total scores. A Cronbach alpha of $\alpha = 0.65$ was found in the study, which is considered acceptable (Hair et al. 1998, Hinton et al. 2014).

3.3.2 Future conventional and electric vehicle purchase model

Two models of household car purchase intention were devised: first, a model on car purchase decision making, and second, a model focusing on car types. The expectation

was that factors collected in the survey, which mainly concerned household characteristics, would influence respondents' car purchase behavior and car type choice.

3.3.2.1 Car purchase decision model

The first model aimed to understand car purchase decisions, relying on household-oriented characteristics. In our survey results, 38% of respondents intended to purchase a car in the two years following the survey, from 2015 to 2017, which is a significantly higher rate than the 21.4% of e-bike users whom the author surveyed regarding car purchase intentions in the national telephone survey the author conducted in 2013 (Ling et al. 2015). The dependent variable was purchase decision for the next two years, which is a binary variable. The independent variables were mainly the subjects' household characteristics. A binary logistic regression model is the most commonly used model in the literature for binary outcomes (Washington et al. 2010). The distribution of plans to purchase a car showed significant variability in the five districts in Beijing that were surveyed ($p < 0.001$). To consider the data at multiple levels, a multilevel mixed-effect logistic regression model and a Bayesian multi-level logistic regression model were also utilized with districts as groups and households as the population. This allowed examination of the effects of district-level and respondent-level variables on purchase decisions while accounting for the non-independence of observations within a cluster (Gelman 2006). Compared to traditional regression models, Bayesian models assume that coefficients follow distributions rather than treating them as fixed values. Bayesian inference also overcomes the issue of overestimated odds ratios occurring when the number of observations is limited (Nemes et al. 2009). The model specifications are shown in the following sections.

Binary logistic regression model

$$\text{logit}(p(x)) = \log\left(\frac{p(x)}{1-p(x)}\right) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_n X_n$$

$$p = \frac{\exp(\alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_n X_n)}{1 + \exp(\alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_n X_n)}$$

where p is the probability that respondents have a purchase plan in the next two years (yes = 1, no = 0); α is the constant, β is the vector of parameters to be estimated, n is the number of independent variables, and $\mathbf{X}$ is the vector of independent variables collected in the survey and consisting of gender, education, job, household vehicle ownership, vehicle purchase history, number of licensed drivers, household income, and other factors. The binary logistic regression model used the maximum likelihood method to estimate the model.

Multilevel mixed-effects logistic regression

$$\text{logit}(P_{ij}) = \log \left(\frac{P_{ij}}{1 - P_{ij}} \right)$$

$$\text{logit}(P_{ij}) = \log \left(\frac{P_{ij}}{1 - P_{ij}} \right) = \beta_0 + \sum_{m=1}^M \beta_m X_{mij} + Z_{ij} U_j$$

where p_{ij} is the probability of a car purchase decision of a household sample i (level 1) in district j (level 2). X_{ij} are household features corresponding to fixed effects, while β_m are the coefficients of the model. Z_{ij} are the covariates corresponding to random effects. U_j represents a district-level random effect. The random effects are not directly estimated as model parameters but are instead summarized as variance components. Estimation of the parameters allows the correlations between households of the same district and between districts to be modeled. They are independent and assumed to be normally distributed: $U_j \sim N(0, \sigma^2)$ (Rodriguez et al. 1995, Goldstein et al. 1996, StataCorp 2013). The maximum likelihood method was used to estimate the model. The data used in this study were organized into two levels. Level 1 is the household level, corresponding to household factors, with 1,216 respondents collected in Beijing city. Level 2 includes the

five districts the survey covered and includes a dummy variable to represent one of the five districts in Beijing.

Bayesian multilevel logistic regression model

$$\text{logit}(P_{ij}) = \log \left(\frac{P_{ij}}{1 - P_{ij}} \right)$$

$$\text{logit}(P_{ij}) = \log \left(\frac{P_{ij}}{1 - P_{ij}} \right) = \beta_0 + \sum_{m=1}^M \beta_m X_{mij} + Z_{ij} U_j$$

where p_{ij} is the probability of car purchase decision of the household respondent i (level 1) in district j (level 2). X_{ij} are household features to which correspond the fixed effects, while β_m are the coefficients of the model. Z_{ij} are the covariates corresponding to the random effects. U_j represents the district-level random effect. Four chains, each with 2,000 iterations, were set up in the Stan which is a platform for high-performance statistical computation. In order to eliminate the influence of the starting values, the first 1000 iterations were set as a warm-up to calibrate the sample and were discarded from the estimate (Gelman et al. 2014). In the model estimation, with no prior knowledge of the value of the parameter for district level, the prior was set as non-informative with zero mean and a large variance, i.e., normal $(0, 10^3)$. According to the Bayesian method, the author used Markov Chain Monte Carlo algorithms rather than traditional maximum log likelihood methods to estimate the model.

3.3.2.2 Car type choice model

The second model was a car type choice model, developed with a multinomial logistic model, and estimating the attributes that would influence the vehicle type choice intentions of respondents who planned to purchase a car in the next two years based on their stated preference survey result (Washington et al. 2010). Among future car buyers (461 respondents) in our sample, 63% of them planned to purchase a CV, 26% were

planning to buy a PHEV, and 11% chose a BEV. The multinomial logistic model was formulated as follows:

$$P(i) = \frac{EXP[\beta_{(i)}X_{in}]}{\sum_{\forall I} EXP(\beta_{(i)}X_{In})}$$

$$P(Y = 1) = \frac{exp(X\beta_{(1)})}{exp(X\beta_{(1)}) + exp(X\beta_{(2)}) + \dots + exp(X\beta_{(n)})}$$

$$P(Y = i) = \frac{exp(X\beta_{(i)})}{exp(X\beta_{(1)}) + exp(X\beta_{(2)}) + \dots + exp(X\beta_{(n)})}$$

where Y is the dependent variable, representing car type choice, including CVs, BEVs, and PHEVs. X is a vector of the possible variables, such as household characteristics, and personal inclination toward EVs. n represents the number of variables. $\beta_{(i)}$ is a set of coefficients corresponding to the i th choice.

3.4 Results, Analysis, and Discussion

3.4.1 Respondent demographics and perception of EVs

The data in Table 3.2 provide sample demographic statistics. Respondents were asked to select their household income within income categories. Gender, age, income per person, and number of cars per person in this Beijing population are also provided in Table 3.2. Since detailed demographic data are not publicly available, the author cannot compare the demographics of the sample and the general population of Beijing exactly in the way the author collected them. Nevertheless, the sample was representative of the population in Beijing according to Table 3.2, albeit with a slightly younger age profile. The average familiarity scores of respondents who intended to purchase a CV, PHEV, or BEV, and respondents who didn't have purchase intentions were 1.80, 1.94, and 1.72 respectively, and statistical different ($p = 0.022$, EVs versus CVs; $p = 0.000$, EVs versus no purchase intention). This confirms that the Chinese public have different levels of understanding of

Table 3.2. Sample characteristics (compared with Beijing City Data)

Sample		Beijing City Data ¹	
Category	Percentage/Number	Category	Percentage
Gender			
Male	58.6%	Male	51.4%
Female	41.4%	Female	48.6%
Age			
<18	4.9%	0-14	9.9%
18-50	88.8%	15-59	75.2%
>=51	6.3%	>=60	14.9%
Annual income per person (1000 Yuan)			
40.58		43.91	
No. of cars per person			
0.21		0.26	
Education			
Middle school or below	3.8%		
High school or technical school	25.2%		
Bachelor	58.0%		-
Master or above	13.0%		
Adults	3.5 (1.1)		
Children	0.6 (0.8)		
Number of licensed drivers			
	1.7 (1.0)		

1. Source: Beijing Economic and Social Development Statistics Year Book 2014, Beijing Statistical Bureau.
2. Standard deviation in parentheses.
3. \$1=6.20 RMB (2015.6). Annual income per person of samples are estimated from mid-points of household income and household sizes.

EVs, which are still a quite new transportation mode in China. People who had an intention to purchase EVs were the group with a better understanding of EVs.

Figure 3.4 shows household vehicle ownership, the parking situation among car owners, and car purchase intentions within the next two years. More than 70% of the respondents owned one or more cars in the household, while 45% of households owned one e-bike or more⁵, and only 24% families owned motorcycles. For household owning car(s), approximately 85% of the respondents parked their cars in a reserved parking space or shared parking space at home, and 78% parked in a reserved or shared space at work. Charging infrastructure is one of the primary barriers to electric vehicles (Zhang et al. 2014, Noell et al. 2016). A reserved parking space at home or at work may be a suitable place for charging an EV. About 43% of the respondents don't have reserved parking space at home and work, which means these respondents don't have access to dedicated charging in their residential district or at work. Figure 3.5 shows household income distributions of CV, PHEV, and BEV three groups, indicating that respondents who planned to purchase a BEV had relatively higher household income compared to other two groups.

Figure 3.6(a) shows respondents' household first car and first e-bike purchase history. Most car purchases happened in the past ten years (especially after 2010) at prices below 250,000 Yuan (\$1=6.20 RMB (2015.6)), corresponding to the rapid increase of motorization in China. Also, a few more high-price purchases (> 250,000 Yuan) happened after 2010.

⁵ In 2002, the Beijing government had proposed a complete ban on e-bikes to come into force on January 1, 2006. However, instead, the government adopted a new e-bike policy, issuing licenses for e-bikes and permitting licensed e-bikes to travel in the city in 2006 (Wells et al. 2015). Ten main thoroughfares in Beijing forbade e-bikes in 2016.

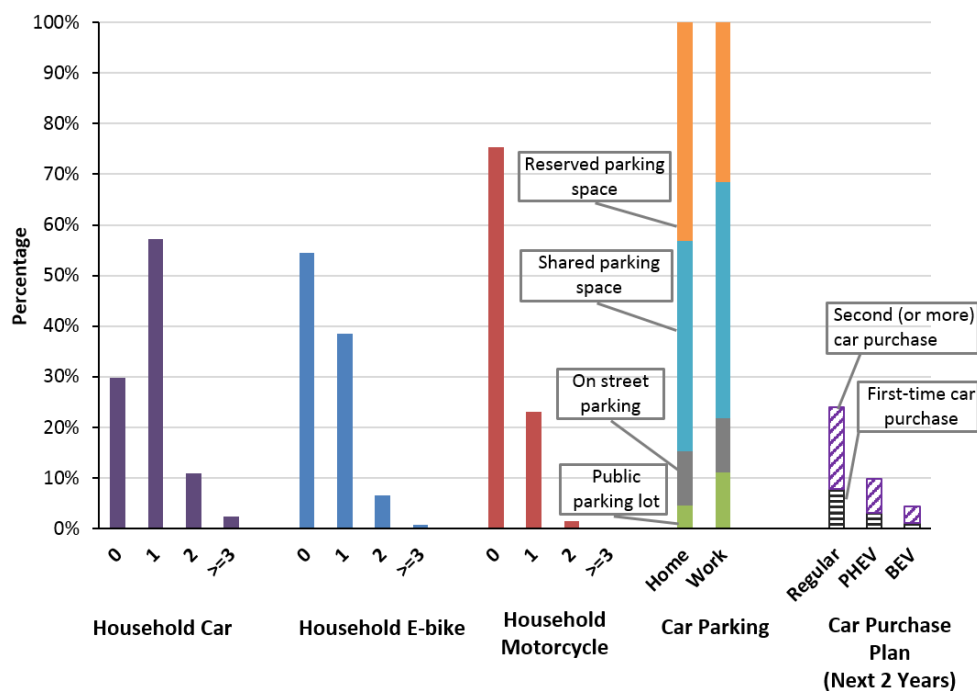


Figure 3.4. Household vehicle ownership, parking, and car purchase intention over next 2 years
(Sample size of Home of Car parking is 821, sample size of Work of Car parking is 783)

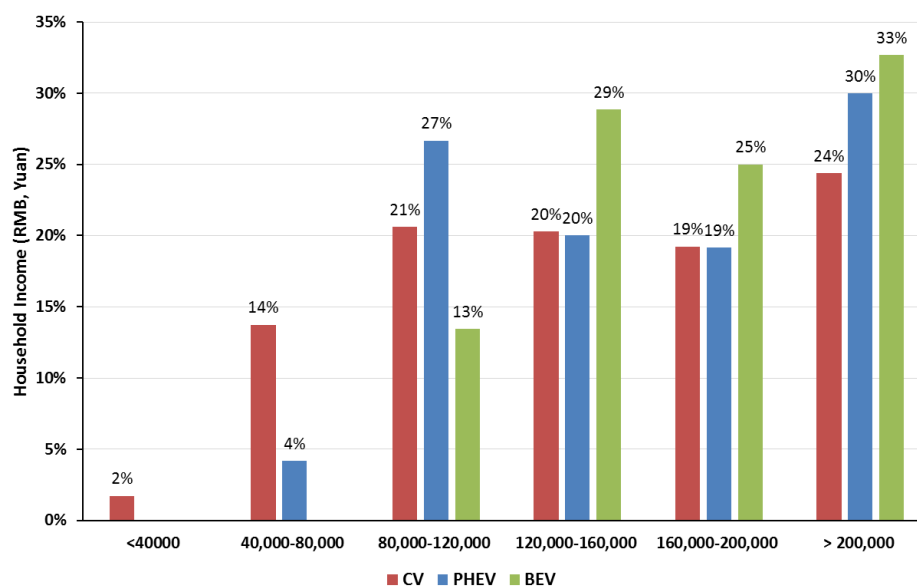
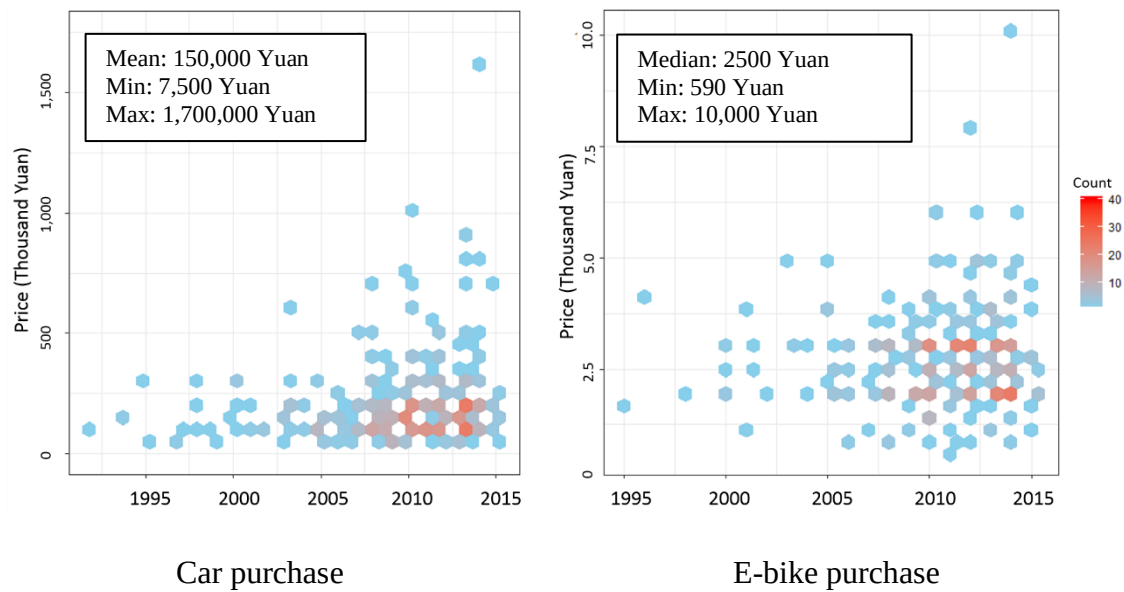


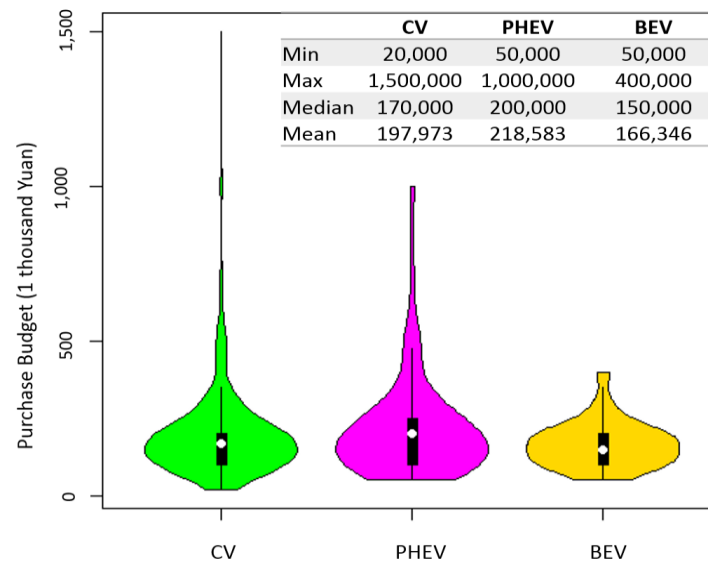
Figure 3.5. Household income distributions of three groups

Interestingly, most e-bike purchases also occurred in the past ten years, with prices ranging from 2,000-4,000 Yuan. This is likely because the Beijing government legalized licensed e-bikes to travel in the city in 2006, and e-bike technology matured in the 2005-2010 period. In the survey, the author inquired as to respondents' car purchase intentions and purchase budget in the next two years. Violin plots are used to show vehicle types and budgets for planned purchases in Figure 3.6(b). White markers represent median budgets for a given type of vehicle, and black boxes indicates the interquartile range of the budgets. A curve shows the kernel density probability density of the purchase budgets at different values. Budgets for CVs and PHEVs covered a wide range, from 20,000 to 1.5 million Yuan, and 50,000 to 1 million Yuan, respectively. For BEVs, the budgets ranged from 50,000 to 400,000 million Yuan. The lower BEV budget may be because potential customers believe BEVs are not worth allocating a higher budget, or because BEVs have more market potential compared to CVs and HEVs among the lower-cost categories in the vehicle market, which gives some hint as to potential EV market promotion and consumer behavior.

Table 3.3 shows potential consumers' understanding and attitudes toward EVs (both BEVs and HEVs). The questions covered four categories, including experience with EVs, general rating, social norms, and consideration of purchase. Respondents who had EV purchase plans had more experience with EVs than did those with no plans to purchase (p -value = 0.010). Also, more people had friends/family or neighbors owning EVs in the potential EV purchase group than in the potential CV purchase group or the no-purchase group (p -value = 0.010, and 0.000 respectively) showing neighbor effect (Al-Alawi et al. 2013). The no-purchase group had the highest general rating of e-bikes but no statistically significant difference. Interestingly, the group interested in CVs rated the EVs the lowest (1.91) among the three groups, statistically lower than the 2.36 of the EV purchase group



(a)



(b)

Figure 3.6. Vehicle purchase history and future purchase budget

(p-value = 0.036). This suggests that those who are making efforts to promote EVs should pay more attention to improving the image of EVs to attract CV customers to the EVs.

When all respondents were asked to rate social status of operating an e-bike, a CV, and an EV, the e-bike got the lowest rating while EV got the highest (Table 3.3). The EV purchase group accorded a significantly lower social status score to driving CVs (5.60), compared to the CV purchase group (6.06) and the no-purchase group (6.02) respectively, while the EV purchase population rated the social status of driving EVs significantly higher (6.81). The EV purchase population had the highest rating (7.52) of the statements, “I would consider vehicle emissions when I plan to purchase a car” and “I have a positive attitude toward EVs because of e-bikes” (6.51), though no significant difference compared to the CV and the no-purchase groups. The EV purchase population rated the statement “Compared to normal car, EV is similar in performance” significantly higher than did the no-purchase group, which suggests that the no-purchase group may have less knowledge of EVs. Interestingly, the EV purchase group had the highest agreement with the statement “I (might) have more mechanical problems with EV than a CV.” When asked to what extent respondents agreed with the statement “I would prefer to drive a normal car to an EV,” the CV purchase group had the highest score (6.10) which was significantly different from the score of 5.06 in the EV purchase group (p-value = 0.000)

3.4.2 Model results

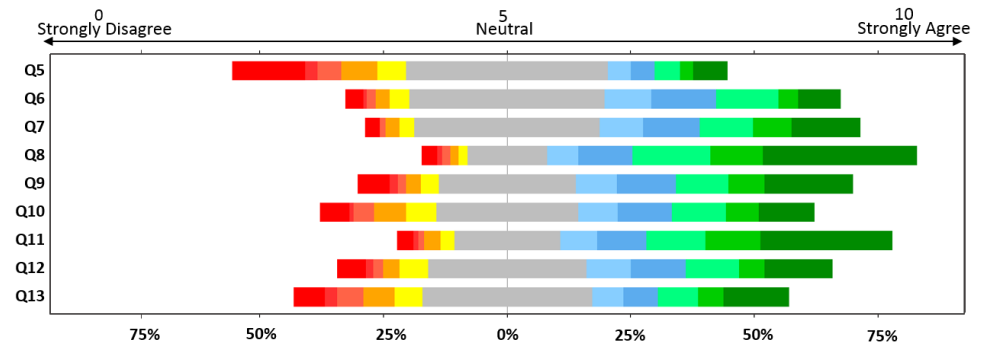
The car purchase plan model was developed with a dependent variable with two possible outcomes, the answer to a “Yes/No” question about whether the household plans to purchase a car in the next two years. About 38% of the households the author collected stated that they planned on purchasing a car within the next two years. The car purchase plan model results are presented in Table 3.4. Some variables were removed because of very low significance levels (p-value > 0.5), such as the number of children, education level, and age.

Table 3.3. Consumers' understanding and attitudes toward EVs

No.	Category	Question	Mean			T-test	
			EV	CV	No	EV vs CV	EV vs no
Q1	Experience with EVs	Have you ever driven or ridden in an EV? (Yes=1, No=0)	0.45	0.38	0.34	0.131	0.010**
Q2		Do you have friends/family or neighbors that own an EV? (Yes=1, No=0)	0.53	0.41	0.38	0.010**	0.000**
Q3	General rating	^a What is your opinion towards e-bikes in general?	1.87	1.81	2.00	0.795	0.532
Q4		^a What is your opinion towards e-vehicles in general?	2.36	1.91	2.20	0.036**	0.374
Q5	Social norm	^b Does driving an e-bike improve your status or self-image?	4.45	4.65	4.55	0.468	0.658
Q6		^b Does driving a CV improve your status or self-image?	5.60	6.06	6.02	0.032**	0.023**
Q7		^b Does driving an EV improve your status or self-image?	6.81	6.27	6.33	0.013**	0.012**
Q8	Purchase consideration	^{b, c} I would consider vehicle emissions when I plan to purchase a car.	7.52	7.31	7.48	0.439	0.859
Q9		^{b, c} I have a positive attitude toward EVs because of e-bikes.	6.51	6.21	6.27	0.269	0.304
Q10		^{b, c} Compared to a normal car, an EV is similar in performance.	6.23	5.80	5.72	0.102	0.019**
Q11		^{b, c} Compared to a normal car, an EV is cheaper over the long term.	7.36	7.16	6.98	0.433	0.117
Q12		^{b, c} I (might) have more mechanical problems with an EV than a CV.	6.25	6.20	5.87	0.842	0.094
Q13		^{b, c} I would prefer to drive a normal car to a EV.	5.06	6.10	5.45	0.000**	0.094

Note:

- Eleven point Likert scale, -5 to +5; -5: Very Negative; 0: Neutral; +5: Very Positive.
- Eleven point Likert scale, 0 to 10; 0: Strongly Disagree; 10: Strongly Agree.
- Questions were asked in the following form: "To what extent do you agree with the following statement?"



All three models performed well and consistently. For the binary logistic regression, the likelihood ratio chi square was 148.67 with a p-value of 0.001, meaning that the binary logistic regression model as a whole was statistically significant. For the multilevel mixed effect logistic regression model, the Wald chi-square was 105.83 with a p-value of 0.000, meaning it was statistically significant. For the Bayesian multilevel model, the Rhat value is the potential scale reduction factor on split chains, showing the convergence status of the Markov chain Monte Carlo algorithm. The Rhat value of each parameter was 1, meaning that all chains had converged with enough iterations. The multilevel mixed effect logistic model performance was better than that of the binary logistic regression model with the smaller BIC value (1586.14 Vs. 1594.11). The three models' results were very close, as can be seen by checking their coefficient estimates, which were identical to two decimals. Concerning interpretability and model performance, the author focused on the multilevel mixed effect logistic regression model to interpret.

The estimated results were generally intuitive and consistent with other studies on car purchase behavior, with some new and interesting findings.

Regarding the fixed effects, household income, and duration of ownership of the first motorized vehicle (e-bike/motorcycle/car) were both positive and significant (p -value = 0.001 and 0.001 separately). Males were more likely to purchase a car in the next two years. The household number of e-bikes was insignificant, while the number of motorcycles was significantly positive (p -value = 0.022)⁶ and the number of cars was significantly negative (p -value = 0.007). The result indicates that the more cars a household owned, the lower probability of purchasing a new one. However, the more motorcycles a household owned, the higher probability of purchasing a car. This suggests that motorcycle owners tend to move to heavier motorized vehicles to replace current

⁶ Although more than 200 cities in China have banned heavy motorcycle over noise, pollution, and safety concerns, Beijing has only some restrictions on motorcycles and allows licensed motorcycles on roads.

vehicles or to supplement current travel demands. Respondents who already had a driver license or planned to have one were significantly positive (p -value = 0.000 for both), and people who already had a license were more likely to purchase a car compared to people who planned to have a license in three years. Families with no motorized vehicles were most likely to purchase a car, followed by families who purchased e-bikes as the first motorized vehicle, compared to families who had motorcycle or cars as their first motorized vehicles, which is consistent with the current early stages of motorization in China.

Considering the random effects, the standard deviation of the intercept at the district level indicates that car purchase fixed effects had little variation across districts.

Car type choice model estimates are presented in Table 3.5. The car type choice model was determined based on the answer to which type of cars would be purchased (with three possible outcomes: CV, PHEV, and BEV) if the household planned to purchase a car in the next two years. Among the sample, 24% of respondents planned on purchasing a CV, 10% a PHEV, and 4% a BEV. The Hausman test and small-Hsiao test were used to test the Independence of Irrelevant Alternatives (IIA) assumption. Both tests follow the H_0 assumption that the odds are independent of other alternatives. A multinomial logit model was used in this analysis. Insignificant variables with high p -value were removed. The likelihood ratio chi-square of 39.54 with a p -value < 0.0001 shows that the model as a whole fit significantly.

In the model, CV purchase intention was set as the reference group. Males' preference for PHEVs relative to CVs increased by 0.40 (weakly significant), while the multinomial log-odds for BEV relative to CV increased by 0.99 (p -value = 0.013). For one unit increase in respondents' personal inclination toward CVs, the multinomial log-odds for PHEV relative to CV decreased by 0.08, while BEV relative to CV decreased by 0.2. Personal experience with EVs, regardless of whether the respondent had driven or ridden before, had a statistically significant influence on BEV purchase as the log-odds for BEV choice relative to CV increased by 0.94.

As the author discussed in the introduction section, more than 20 cities have EVs, mainly in the form of BEV pilot projects. The result shows that these pilot projects may contribute to respondents' EV experience. Also, the sample may suffer from self-selection bias which means people who rode/drove in an EV may have an inclination towards an EV. Respondents who planned to have a driver license within three years had a negative and marginally significant influence on PHEV. Similarly, respondents who already had a driver license showed a negative and marginally significant influence on BEV choice relative to CVs. Household income was found to positively influence PHEV and BEV choice, respectively. For every 10,000 Yuan increase of household income, the log-odds for PHEV relative to CV increased by 0.22 (p -value = 0.018), while choice of BEV relative to CV increased by 0.53 (p -value = 0.001).

However, purchase budget had a significantly negative influence on BEV relative to CV. This shows that high-income families may be more likely to purchase BEVs, but not with a high purchase budget, indicating that potential customers may still be concerned with BEV value, which is consistent with the descriptive results.

The number of e-bikes had a positive and weakly significant influence on PHEV preference relative to CV (p -value = 0.065). However, the number of e-bikes was insignificant on the BEV purchase plan. It seems that e-bike use' experience and benefits pushed respondents toward PHEV purchase relative to CV. However, it is not clear that their experience with charging and the potential range challenges of e-bikes discouraged BEV preference. The duration time of first motorized vehicle ownership was negative and weakly significant on PHEV relative to CV, while a motorcycle as the first motorized vehicle was positive and weakly significant.

Table 3.4. Models' results for purchase plan

Logistic Regression Model		Binary		Multilevel mixed effect		Multilevel Bayesian	
Factors		Coef.	p-Value	Coef.	p-Value	Coef.	95% Credible intervals
		<i>Fixed effects</i>				<i>Population-level effects</i>	
Constant		-2.71	0.00***	-2.20	0.00***	-2.57	(-3.82, -1.68)
Gender (Male=1, Female=0)		0.35	0.01***	0.34	0.01***	0.34	(0.07, 0.61)
Driver license							
Already have license		1.66	0.00***	1.66	0.00***	1.62	(1.14, 2.13)
Plan to get license		1.10	0.00***	1.11	0.00***	1.06	(0.55, 1.58)
No plan at all		base		-	-		
Emission concern (Not Concerned=1, ... Very Concerned=10)		-0.13	0.36	-0.13	0.37	-0.13	(-0.41, 0.14)
No. of licensed drivers		0.15	0.06*	0.15	0.06*	0.16	(0.00, 0.32)
Household income		0.03	0.00***	0.03	0.00***	0.03	(0.02, 0.05)
No. of e-bikes		0.12	0.38	0.11	0.40	0.13	(-0.07, 0.33)
No. of motorcycles		0.34	0.02**	0.34	0.02**	0.19	(-0.06, 0.44)
No. of cars		-0.34	0.01***	-0.33	0.01***	-0.39	(-0.62, -0.18)
Duration of first motorized vehicle ownership in months		0.06	0.00***	0.06	0.00***	0.04	(0.01, 0.08)
E-bike is the first motorized vehicle (Yes=1, No=0)		-0.48	0.10	-0.48	0.10	-0.47	(-1.04, 0.09)
Motorcycle is the first motorized vehicle (Yes=1, No=0)		-0.96	0.01***	-0.94	0.01***	-0.93	(-1.61, -0.27)
Car is the first motorized vehicle (Yes=1, No=0)		-0.54	0.05**	-0.54	0.05**	-0.54	(-1.08, 0.01)
District				<i>Random effects</i>		<i>Group-level effect</i>	
1		base		Intercept of District		Intercept of District	
2		0.44	0.03**	Variance	Std. dev.	Variance	
3		0.94	0.00***	0.09	0.08	0.38	(0.15, 2.51)
4		0.96	0.00***				
5		0.38	0.04**				
Goodness of fit		LR chi² =148.67		Wald chi² =105.83		Rhat of each	
		P > chi² = 0.001		P > chi² =0.000		parameter: 1	
BIC		1594.1		1586.1			

*** Denotes that estimate is statistically significant at the 1% level. ** Denotes that estimate is statistically significant at the 5% level. * Denotes that estimate is statistically significant at the 10% level.

Table 3.5. Multinomial logit model results of car type choice behavior

Factors	Coefficient	Std. err.	Z-value	p-value
CV	Base outcome			
PHEV				
Gender (Male = 1, Female = 0)	0.40*	0.26	1.56	0.120
Personal inclination to CV (Likert scale, Not at all: 0, ..., Definitely yes: 10)	-0.08**	0.04	-1.85	0.064
Plan to have a driver license in 3 years	-0.87*	0.58	-1.50	0.135
Household income (in 10,000 Yuan)	0.22***	0.09	2.37	0.018
No. of e-bikes	0.37**	0.20	1.85	0.065
Duration of first motorized vehicle ownership (years)	-0.04*	0.03	-1.50	0.134
First motorized vehicle is a motorcycle (yes = 1, no = 0)	0.72*	0.46	1.55	0.121
Constant	-1.42*	0.88	-1.62	0.105
BEV				
Gender (Male = 1, Female = 0)	0.99***	0.40	2.47	0.013
Personal inclination to CV	-0.20*****	0.06	-3.32	0.001
Drive or ride EV before (Yes = 1, No = 0)	0.94*****	0.35	2.71	0.007
Already have a driver license	-1.34**	0.70	-1.91	0.056
Household income (in 10,000 Yuan)	0.53*****	0.15	3.48	0.001
Purchase budget (in 1,000 Yuan)	-0.01***	0.00	-2.51	0.012
First motorized vehicle is a car (Yes = 1, No = 0)	0.64	0.44	1.44	0.150
Constant	-2.70***	1.23	-2.20	0.028
LR $\chi^2(22) = 39.54$	Prob > $\chi^2 = 0.000$			
Log likelihood at convergence = -371.593	Sample size: 464			

**** Denotes estimate is statistically significant at the 1% level. *** Denotes estimate is statistically significant at the 5% level. ** Denotes estimate is statistically significant at the 10% level. * Denotes estimate is statistically significant at the 15% level.

3.4.3 Policy implications

Respondents were asked to choose three preferred EV promotion policies among ten possible promotion policies the author provided. The results are shown in Figure 3.7. Of the respondents, 52% chose purchase subsidies and more charging stations, indicating that the public prefers direct purchase cost reduction or monetary subsidy and more advanced infrastructure service. Currently, both central and local governments provide one-time purchase subsidies to EV buyers. Free battery charging was ranked third among possible promotion policies, showing that people are concerned about maintenance or use expense. However, although free battery charging may be effective in promoting EVs for a short period, it may not be a sustainable long-term strategy. The next highest, 34% chose license plate restriction waivers. Beijing has been using traffic restrictions based on the last number on license plates for ten years to reduce car trips and shift travelers to public transit trips. License plate restriction waivers can be a good way to give some advantage to EVs, but they undercut the original purpose of congestion mitigation. EV insurance benefits, purchase tax exemptions, license fee exemptions and free parking ranked fifth to eighth. Only 19% of the respondents chose reserved parking spaces, and 8% chose emission restrictions.

As the author summarized in the introduction section, the Chinese government has various policies covering seven aspects of NEV promotion. The author focuses on recommendations based on customers' preferences and demand to attract more potential CV customers to transfer to EVs. The author found that customers are more interested in direct monetary benefits and daily use benefits, such as purchase subsidies, and easy access to free charging stations. These policies should be given a high priority for promotion. Besides dedicating great effort to improve charging infrastructure, the author also recommends a charging discount to attract more potential CV users to EVs. For daily use benefits, waiving the license plate restriction is recommended with the caveat that it not exacerbate congestion problems. Also, exempting EVs from minimum occupancy

requirements on HOV lanes may increase EV sales (Diamond 2008, Gallagher et al. 2011, Jin et al. 2014).

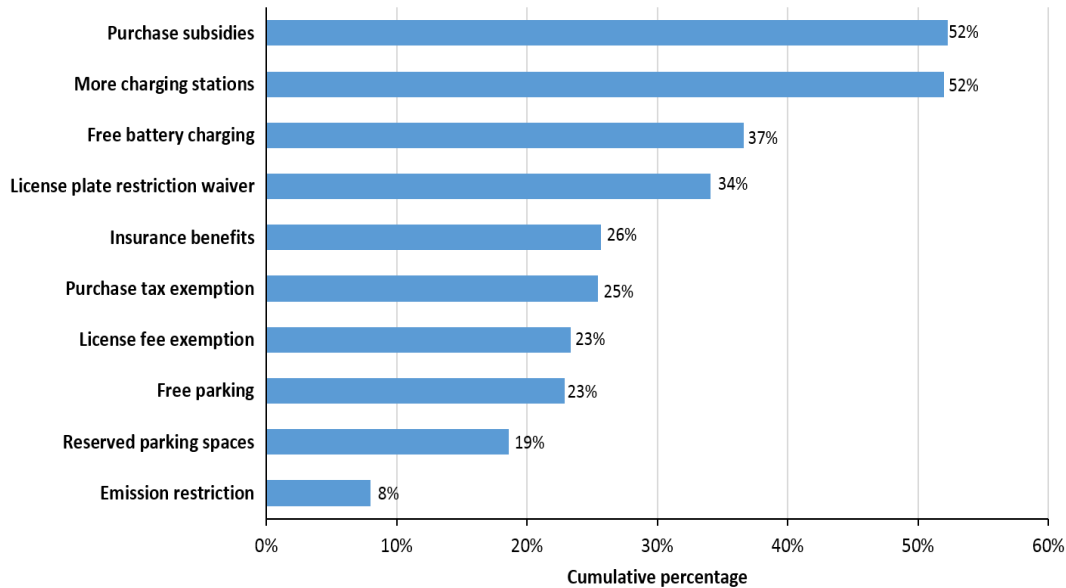


Figure 3.7. Preferred top 3 EV promotion policies

The author also found that future EV customers are only willing to allocate a relatively low budget to potential BEV purchases, though future BEV customers' household income is relatively high, probably because they are concerned about the potential risk of unsound EV technology and service, or they may have low expectations because of their experiences with low-cost e-bikes. The author suggests that the EV market, especially the BEV market, should target the mid-level and below markets, and focus less on the top-end market. The mid-level and below markets for EVs could encourage more future CV customers with relatively low budgets to lean toward EVs with if central and local government subsidies are in place. In terms of limited land use and parking issues, as well as manufacturing costs, the author also suggests the promotion of micro EVs. "Micro EVs" here refers to compact or small-sized and well-configured EVs, rather than

the low-speed, poorly configured micro EVs that are currently popular in some areas of China. But the top-end market also needs attention since it can help raise the social image of EVs and satisfy the needs of high earners who desire to gain respect as protectors of the environment, or for whom acting in an environmentally friendly way is important to how they see themselves. Social status in the top end of the EV market could improve the public's impression of EVs, which may result in increased personal inclination to purchase an EV.

The experience of previously riding or driving in an EV had a statistically positive influence on BEV purchase intention. As a variable that can be influenced externally, familiarity and experience with EVs can be improved in many possible ways. Although over 25 Chinese cities have had pilot EV projects, more pilot projects are suggested in order to cover wider areas. Also, test-driving and free driving activities are also likely to benefit EV promotion because they would add to the statistically significant effect of previous experience. As China is in a rapid burst of motorization, and electric mobility is still in the early phase, encouraging more potential gasoline vehicle users to switch to EVs now is more important and meaningful than switching current gasoline vehicle users to EV use in the future.

3.5 Conclusion

This study targeted the public's future car purchase plans, especially planned vehicle type choice, with the goal of identifying potential customers' attitudes toward and perception of EVs, as well as variables that will influence their car purchase decisions in the future, in order to make policy suggestions from customers' perspective. This paper adds to the growing body of literature investigating vehicle purchase, focusing on factors influencing PHEV and BEV purchase decisions. Compared to CV purchase, being male and having a high household income increased respondents' chances of purchasing EVs (PHEV or BEV). Personal inclination toward CVs decreased the chances of purchasing EVs. Besides these common attributes, plans to get a driver license over the next 3 years decreased respondents' possibility of purchasing PHEVs. The household number of e-

bikes increased the chances of purchasing PHEVs. The longer respondents had owned a first motorized vehicle, the lower were their chances of purchasing PHEVs. Prior experience with driving or riding in an EV increased the chances of purchasing BEVs. Already having a driver license and a high purchase budget also decreased the chances of purchasing a BEV.

Respondents were classified into three groups based on future vehicle purchase plans, including. The author found that statistical differences existed among the three groups (people plan to purchase a CV, an EV, or no plan to purchase a vehicle) in experience with EVs, general rating of EVs, and social status associated with CVs and EVs. A further finding was that the top three preferred EV promotion policies included purchase subsidies, more charging stations, and free battery charging, while another highly confirmed policy recommendation was license plate restriction waiver (chosen by 34% of respondents). Policy recommendations from customers' perspective are therefore offered based on the results, and can be summarized as follows: direct monetary benefits and daily use benefits, effective advertising of promotion policies, focusing on mid-level and below market, with some focus on the top-end market, encouragement of social status influence, development of well configured micro EVs, and test-driving and free-driving activities to increase experience.

The two main limitations to this study are first, that the sample included only respondents from Beijing, which did not allow us to estimate different local government policies or the public's attitude and intention to buy EVs. Secondly, the author did not survey or evaluate respondents' different perceptions of PHEVs and BEVs in Likert-scale question form because of survey length limit.

CHAPTER 4

**EMERGING MICRO ELECTRIC VEHICLES IN CHINA: USE
MOTIVATION AND EXPERIENCE**

Abstract

As the Chinese government promotes new-energy vehicles (i.e., electric or battery-powered rather than gas-consuming vehicles), micro electric vehicles (MEVs) are gaining popularity in many areas in China (~ 4 million ownership). However, their adoption has been controversial. While there have been many studies focused on new energy vehicle acceptance, purchase intention, and driving behavior; little research has focused on MEVs. This paper uses qualitative methods to investigate the motives for MEV choice and purchase, user experience, safety issues and perception of safety, as well as vehicle status. In-depth interviews with MEV owners in Kunming, China reveal that MEV users are predominately retired males with high household income. The average range of their MEVs' is about 100 km, with a maximum speed from 40 to 60 km/h. Less than half of users have a driver license. Their purchase motives are mostly driven by their age or physical limitations, the convenience and low cost of the vehicle and charging, and the vehicles' low speed. Most users had transitioned from using e-bikes and public transit. About half of the respondents have had crashes during the average ownership duration of 3 years. Surprisingly, none of the respondents were concerned about safety issues and were relatively ignorant about traffic safety procedures. Based on these results, we look at policy implications and offer recommendations, including standardizing MEVs, imposing a license system for MEVs and their users, enhancing traffic management, and strengthening the insurance system. Despite their shortcomings, MEVs can be an efficient traffic mode for many people to meet their personal travel needs using cleaner energy, limiting emissions and reducing safety risk

4.1 Introduction

With considerable economic growth and technology development, China is rapidly experiencing motorization and a dramatic expansion of the transportation system (Ling et al. 2015). At the same time, because of environmental concerns and the challenge of generating cleaner power, electric vehicles, including two wheel-vehicles, has received widespread and powerful support from the Chinese government. Even a cursory glance at

electric vehicle sales in the domestic Chinese market reveals a booming transportation system. Since 1998, about 300 million electric bikes (e-bikes) have been sold in China (National Bureau of Statistics 2012b, Ling et al. 2015), and since 2013, there has been a rapid expansion of sales of electric four-wheeled vehicles (China Association of Automobile Manufacturers 2014a, New Energy Vehicle Association 2014, Association of Beijing New Energy Automotives 2015, China Auto Association 2017, Ou et al. 2017). Aside from e-bikes, which are heavily used in the Chinese transportation system, and conventional electric four-wheeled vehicles which have been strongly supported by the Chinese government, a micro electric vehicle (MEV) is emerging in many areas in China without strong incentives and support given to most “New Energy Vehicles.” The MEV is a lightweight and low-speed battery-powered electric vehicle with three or four wheels as shown in Figure 4.1. According to uncompleted statistics, more than 600,000 MEVs were sold in 2015 in China, and 610,000 MEV were sold in Shandong province alone in 2016 (Auto 163 2016, 2017). The sales of MEVs have increased rapidly for various reasons, including their modest price, small size, no requirement of charging piles, and other reasons.



Figure 4.1. Micro electric vehicles (Source: Corporate product websites)

However, this technology has also brought controversy regarding market regulation, traffic control, and safety concerns (Auto 163 2016, Chengdu Business Newspaper 2016). In Mianyang, a city in Sichuan province, 268 crashes involving MEVs occurred in the urban area in 2015 (Chengdu Business Newspaper 2016). The government's views about MEVs and their effect on the traffic system seem to be ambiguous. At the end of September 2017, the Ministry of Industry and Information Technology of the central

government excluded MEVs from the newest new-energy vehicle promotion and application vehicle type catalogue; that exclusion means that MEVs are not legal new-energy vehicles (Ministry of Industry and Information Technology 2017). In June 2017, however, Henan Province announced regulation of MEVs, encouraging the development of the industry (ddc.net 2017). Some cities and areas have banned MEVs, citing traffic safety concerns (Zhao 2016). However, policies throughout China are haphazardly determined and implemented with little empirical study exploring MEVs' role in the transportation system, people's experience with their use, or potential safety problems. Also, little is known about MEVs' value as an innovative technology for urban transport. The market led development of MEVs is following similar paths as the early market for e-bikes (Weinert et al. 2007a).

To the author's knowledge, this paper is the first study focusing on MEV owners' daily use experience, perceptions, and motives, and will provide evidence and support for transportation planning and regulation. This study tries to answer following questions: Who purchases and uses MEVs? What are their motives for MEV purchase? Why do MEV users switch from traditional transportation modes to MEVs? What are users' perceptions of the safety of MEVs? Are MEVs simply appropriate for older users or are they an appropriate technology for more general urban transport? To answer these questions, the author interviewed 34 MEV owners in depth using a semi-structured interviews formats. The remainder of the paper is organized as follows: The background section introduces MEVs, e-bike mode shift and behavior in transportation system, and conventional electric vehicle studies. The data collection section discusses data source, and presents the demographic characteristics of the respondents. The result, analysis, and discussion section presents results and discussion on MEV use, experience, and perceptions. The conclusion section presents policy implications, future work of the study, and limitations.

4.2 Background

4.2.1 MEV background

Small size electric vehicles include two main types: conventional electric vehicles of smaller sizes (e.g. A-class vehicles) and low-speed micro electric vehicles. The former is supported by the Chinese government “New Energy Vehicle” plan but still suffers from low sales. The latter (MEV) currently is defined as a low-speed electric vehicle and is excluded from the latest catalogue of new-energy vehicles issued by the central government (Ministry of Industry and Information Technology 2017). However, MEVs are gaining popularity, with over a million sales estimated in 2016 in China⁷, while 0.5 million conventional new-energy vehicles were sold in the same year. (Auto 163 2016, China Auto Association 2017). Though both types of small electric vehicles are different in some ways, they share many common attributes, including vehicle motor power, likely users, and probable future roles in the transportation system. In this paper, the author focuses on MEVs with some discussion about conventional EVs based on our study.

For the purposes of this paper and as shown in Figure 4.1, a micro electric vehicle (MEV) is a battery electric vehicle that is usually built to have small size and a top speed of 40-70 km/h (25-43 mph). With an average energy consumption of 6-10 kWh/100 km⁸, MEVs offer efficient and low-cost transportation with extremely low local air pollution. Different areas have different adoption rate of MEVs. An online search regarding MEV popularity by the author has shown that MEV use is popular and still increasing in Shandong Province, Henan Province, Yunnan Province, and other areas. A MEV is larger and faster than a neighborhood electric vehicle (NEV) in the U.S. An NEV is defined as a four-wheeled vehicle with a top speed of 32 to 40 km/h (20-25 mph), and has a gross

⁷ It lacks official statistics.

⁸ Taking a respondent’s MEV as an example, battery capacity is 60 V, and 48 Ah. Battery range is 90 km. Assuming charging efficiency is 60%, and discharging efficiency is 80%, the MEV energy consumption is $60 \text{ V} \times 48 \text{ AH} / 60\% / 80\% / 90 \text{ km} \times 100 = 6.25 \text{ kWh} / 100 \text{ km}$. For reference, e-bikes in China consume about 2kWh/100km. The Nissan Leaf consumes about 25 kWh/100km

vehicle weight less than 1,400 kg (Electronic Code of Federal Regulations 2017). NEVs are restricted in their operation on streets by their highest maximum speed. In China, there is a lot of controversy about the safety of MEVs on the road since driving an MEV doesn't currently require a driver license, registration, or license plate. Nevertheless, there is little research focusing on MEV use in China or similar vehicles in other countries.

4.2.2 Technology adoption

E-bikes have been a substantial part of the Chinese transportation system since around 2007, with over 150 million on the road today (Weinert et al. 2007b, Jamerson et al. 2013a). E-bikes are popular partly they provide low cost, personal travel flexibility, and accessibility, and little human effort for trips. In addition, some pivotal Central government policy decisions have helped e-bike use boom. In 1999, a national standard of e-bikes was established by the central government on the manufacture of e-bikes, specifying speed limitation, weight and power of e-bikes (Wells et al. 2015). In 2004, a "Road Traffic Safety Law" defined e-bikes as non-motorized vehicles and permitted road users to use them without a driver license. These actions triggered a boost in the e-bike market and e-bike users (Wells et al. 2015). After 2010, e-bike annual sales in China had risen to around 25-30 million. However, many cities eventually banned or restricted e-bikes, citing traffic and safety concerns, as shown in Table 4.1, as more after 2009. Still, though there is little consensus about whether e-bikes are really more dangerous than other traffic modes (Yang 2010, Bai et al. 2013, Du et al. 2013, Cherry et al. 2016) .

New energy vehicles are the other mainstream vehicles that rely (at least partially) on electric power. NEVs, mainly including hybrid electric vehicles and battery electric vehicles, are currently being discussed as an effective means to solve a range of energy and environmental problems. In 2016, the new energy vehicle market share was about 2% of the 24 million passenger cars sold in China market (China Auto Association 2017, Ou et al. 2017). With great effort and the support of various government policies, the NEV market is increasing rapidly. All of the government's new-energy vehicle-related

policies can be classified into seven categories: macroscopic policies, demonstration policies, subsidization policies, preferential tax policies, technical support policies, industry management policies, and infrastructure policies (China Automotive Technology and Research Center 2015, Li et al. 2016).

Table 4.1. Cities banning or restricting electric bikes. Source: Adapted from (Yang 2010)

2001	Wuhan banned electric bikes from city roads
2003	Fuzhou banned the sale of electric bikes
2005	Zhuhai banned electric bikes from entering the city
2006	Guangzhou suspended issuing licenses for electric bikes and banned electric bikes from entering the city.
2007	Changzhou suspended issuing licenses for electric bikes, and scheduled all existing licenses to expire in 5 years. Dongguang banned electric bikes from entering the city.
2008	Shenyang banned from city downtown.
2009	Shenzhen banned electric bikes from certain zones in the city. Changsha suspended issuing licenses for electric bikes purchased after May 1, 2009.

4.2.3 Electric vehicle-related studies

E-bikes, as the largest representative of alternative fuel vehicles, have drawn a wide audience and attention from global researchers since the early 2000s (Cherry et al. 2007b, Weinert et al. 2007b). Generally, e-bike studies focus on transportation mode choice and shifts among modes, environmental effects, and safety, which have been an issue for large numbers of e-bikes in Asian countries (e.g. China) (Ling et al. 2017). Most European and North American studies have been published in the recent six years and focus on influence on health, the benefits for aging population, and their emerging market, i.e. that the e-bike market is driven by high-income earners who are often well-educated older adults (Ling et al. 2017).

Electric car-related studies have focused on consumer adoption behavior and purchase intention because of the current low market share of electric cars (Rezvani et al. 2015). Most of these studies have explored factors influencing alternative fuel vehicle purchase

intentions in developed countries and regions (Rezvani et al. 2015). Stated preference (SP) surveys are widely used to collect data.

In general, much research has been conducted on e-bikes and electric cars focusing on different aspects. However, there is little information about who is using MEVs or how they are using such vehicles. This type of vehicle fills a potential niche between e-bikes and conventional e-cars.

4.3 Data collection

The fact that MEV users are relatively few makes it difficult to do a large-scale quantitative study. As an exploratory study, aiming to understand this nascent market, I performed a semi-qualitative study, using semi-structured interviews to understand MEV users' experiences. This method, often used when little is known about a particular aspect of travel behavior or road users, allows researchers to get an early glimpse into MEV users' behavior and perceptions. This approach has been used in recent e-bike studies in North American and Europe to gain additional insights that traditional survey approaches do now allow (Popovich et al. 2014).

The data collection is conducted in Kunming, the capital of Yunnan province. The city's population is about three million. E-bikes are a substantial transportation mode in Kunming, more than one million. Kunming has high quality bus systems, a Bus Rapid Transit (BRT) system spanning nearly 100 km, and a 90 km subway system. To reduce traffic congestion and noise, and increase safety, motorcycles are heavily restricted in the urban core. In 2010, Kunming had 1.3 million registered motor vehicles; an average ownership rate of > 200 vehicle per thousand population, approximately five times of the national average (National Bureau of Statistics 2010).

For the study, the author employed a two-step recruitment method. First, the author posted advertisements and distributed flyers on notice boards in public places and in community parking lots and at MEV dealerships in Kunming city. About 500 copies of

the flyers were distributed during July of 2016. Second, using a snowball sampling approach, we asked each MEV owner who contacted us to refer other MEV users in the city. A total of 58 adult MEV owners contacted us and accepted face-to-face interviews. Of those, 34 MEV owners completed all questions. Most of them lived in the urban area, and some were from the urban-rural fringe area. Semi-structured interviews were conducted, and survey questions were developed following the format of previous related studies (Johnson et al. 2015, Jones et al. 2016). Figure 4.2 presents an overview summary of the interview themes and survey questions. The semi-structured interviews took about a half-hour each and focused on respondents' motives for purchase, use experiences, mode choice, safety perception of MEVs, vehicle status, future usage, and users' demographics. Pilot surveys were conducted by the team. The author found most respondents spoke Mandarin Chinese with a very heavy local accent. To conduct the interviews efficiently and precisely, two senior undergraduate students were recruited from a local university and trained to do interviews. A surveyor led interviews with MEV users, and the other surveyor wrote down answers and audio-recorded interviews on a smartphone. We offered 50 RMB (7.5 USD) cash to each participant as an incentive. All records and quotations in this study are presented anonymously to protect respondents' identity.

4.4 Results and discussion

4.4.1 Demographic characteristics

Table 4.2 shows the socio-demographic characteristics of the MEV users. The median age was 71 years, and of the 34 respondents, 91% were male and 9% were female.

During the survey, surveyors tried to keep the sample balanced in gender and age. However, on the basis of site observation and discussion with MEV dealers, the author found the proportion of male and female e-bike users is not balanced, and that MEVs were most popular among the old age group, especially among users older than 70 years.

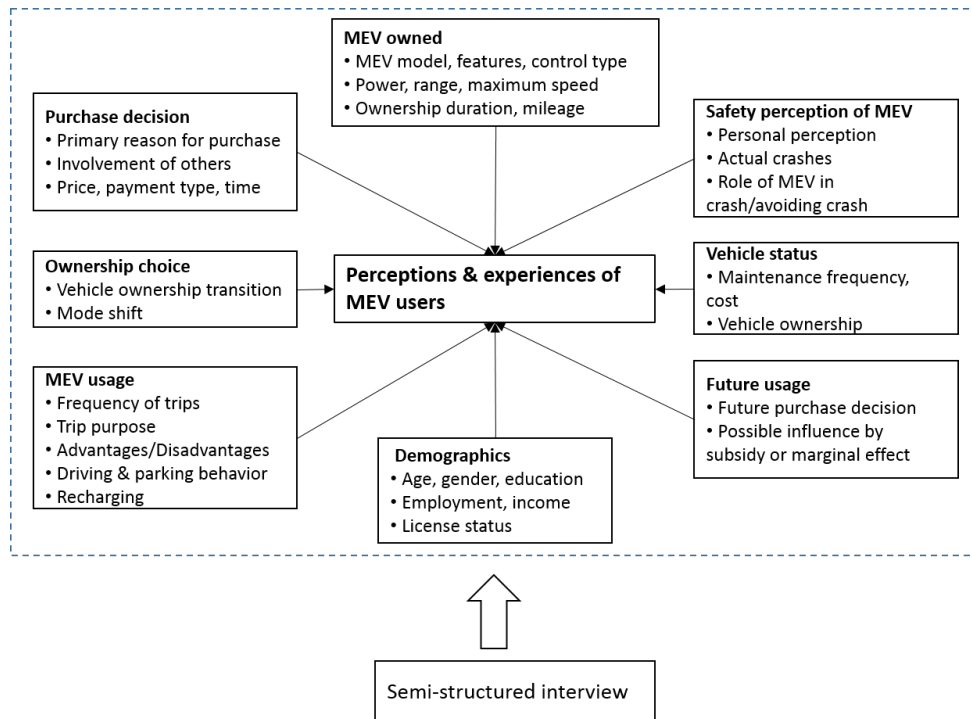


Figure 4.2. Structure of interview of MEV users

Most users had a high school or higher education, 59% with high school and 18% with bachelor's or higher degrees. The average household size was about 4.2 people, including 0.8 children and 1.4 licensed drivers. The average household conventional vehicle ownership was 0.8, with 1.3 e-bikes, and 0.2 bicycles. About 38% of the respondents' annual household incomes were between 100,001 and 140,000 RMB (6.7 RMB = 1 USD), and 32% had incomes higher than 140,000 RMB, compared with an average Kunming household income of 83,341 RMB, according to the Kunming statistical yearbook for 2016. These data imply that MEV users are mainly older, male, and have relatively high household income. In addition, more than 90% of the respondents were retired, 15% had physical limitations, and only 41% had driver license. As there are no available data on the population of MEV users to compare with our sample, it is not clear whether it is representative of all MEV users or biased by the non-random sampling method. But this is the first research paper taking an early look at MEV users which

could provide value to public-sector and government decision makers regarding MEV ownership and management.

4.4.2 *MEV ownership choice*

Characteristics of MEVs

The self-reported characteristics of the respondents' MEV types and models are shown in Table 4.3. All MEVs are fully battery electric vehicles including lithium or lead-acid battery types. The average size of MEVs is 2.3 meters long, 1.3 meters wide, and 1.5 meters high. Of the 34 models of MEVs, 35% are three-wheeled vehicles, and 65% four-wheeled vehicles. Most MEVs have three seats in the vehicle; 12% have two seats, and 18% have four seats.

The sample included two ways in which MEVs are driven; 47% have motorcycle-type handle-bars and 53% have steering wheels. The average reported range is close to 100 km, with 25 km standard deviation. Nearly 40% of MEVs have a maximum speed lower than 40 km/h, 30% between 41 and 50 km/h, and 32% between 51 and 60 km/h. Thus, in contrast to conventional vehicles, the sampled MEVs are low-speed, low-range, fully battery-powered electric vehicles.

Their average price is 15,409 RMB, with the highest price being 31,000 RMB and the lowest price 4,680 RMB. At the time of the survey in July 2016, the average ownership duration was 3.1 years, with the longest duration being 7.3 years and the shortest duration being 0.2 years; most vehicles had been purchased in the past five years and were in generally good condition.

Purchasing decision

One of the key objectives of the study was to identify the factors motivating people to acquire an MEV. Two questions were asked: one was about the primary purchasing reasons, and the other was about the reasons for not choosing a car (Figure 4.3).

Table 4.2. Socio-demographic characteristics of participants

Individual characteristics		Household characteristics	
Gender- male	31 (91%)	No. of adults	4.2
Age		No. of children	0.8
<= 50	1 (3%)	No. with driver license	1.4
51 -70	15 (44%)	No. of conventional vehicles	0.8
>70	18 (53%)	No. of e-bikes	1.3
Median Age	71	No. of bicycles	0.2
Education		Income (before tax, RMB)*	
Middle school	8 (24%)	<= 60,000	4 (12%)
High school	20 (59%)	60,001-100,000	6 (18%)
Bachelor's or higher	6 (18%)	100,001-140,000	13 (38%)
Job status -Retired	32 (94%)	> 140,000	11 (32%)
Driver license (Yes)	14 (41%)		
Physical limitation	5 (15%)		

Total sample size: 34

Note: * the average household income of Kunming is 83,341 RMB (Statistics 2016).

Table 4.3. Characteristics of MEVs

	Average/count (Std./percentage)		Average/ count (Std./percentage)
Length (m)	2.3 (0.3)	Range (km)	98.5 (25.2)
Width (m)	1.3 (0.2)	Maximum speed (km/h)	
Height (m)	1.5 (0.2)	≤40	13 (38%)
No. of wheels		41-50	10 (30%)
3	12 (35%)	51-60	11 (32%)
4	22 (65%)	Battery type	
No. of seats		Lithium	7
≤2	4 (12%)	Lead-acid	21
=3	24 (71%)	Price (RMB)	15, 409 (7,590)
≥4	6 (18%)	Ownership duration (years)	3.1 (1.8)
Control type			
Handle bars	16 (47%)		
Steering wheel	18 (53%)		

Respondents care use benefits and financial benefit of MEV mostly. The majority of respondents stated convenience as their primary reason for choosing an MEV, followed by safety, and their own age or physical limitations with regard to getting a driver license or riding an e-bike. Also more than 20% of respondents chose an MEV because the MEV's low speed was suitable for them, not too fast or too slow. Nearly 20% of the respondents believed that MEVs were inexpensive to purchase and charge. Only 9% of respondents chose an MEV because of environmental concerns. The results showed that MEVs are an efficient and effective travel mode for users, especially for older people. The following comments from respondents illustrate these points:

- “It is like a conventional car with lower speed.”
- “I am too old to ride an e-bike, and e-bikes are not safe. The MEV is much safer than an e-bike.”
- “It is very convenient, and the price is low. It can cover my daily trips, which are usually within 5 km. The MEV is well-configured.”
- “I am old, I can't ride an e-bike. The charging fee for an MEV is very cheap.”
- “The speed is suitable for me, and the charging fee is cheap. It is safe for me to pick up my grandchildren from school.”

Respondents said that they did not choose cars because cars cost too much, were unsafe, went at too high a speed, and were harmful to the environment (Figure 4.3). Also, some respondents were too old to get a driver license or drive a car. Some of them didn't need to travel enough to justify owning a car. Most respondents believed that MEVs met their daily trip needs in a cost-efficient way, meaning the purchase and maintenance costs were lower than those of conventional vehicles. The following comments from respondents highlight these points:

- “Electricity charging is much cheaper than gasoline.”
- “It puts a lot of pressure on me to use a conventional car, including from both monetary and physiological aspects. I don't need to make car trips.”

- “Driving a car needs a driver license. I can’t have a driver license because of my age⁹. Also I don’t need to drive a car.”
- “A conventional car costs too much and is harmful to the environment.”

About 20% of users said that they bought their MEVs after being advised to by a close friend or family member who had a MEV. The other 80% of users purchased their MEVs directly with no influence from anyone else.

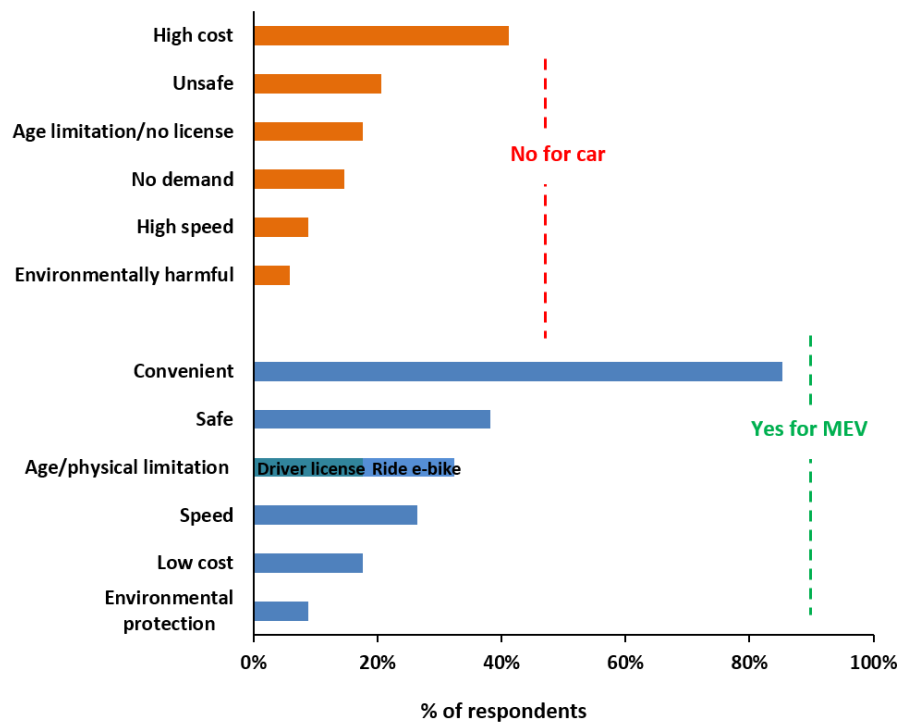


Figure 4.3. Primary reasons for choosing MEV and not choosing car

⁹ Age limitation on getting a conventional car driver license is 70 years old in China

Future purchase

About 65% of respondents would not purchase an MEV again in the future because they were already old and would not need another one. Thirty-five percent of respondents planned to purchase an MEV in the future since they were satisfied with their current MEV's performance.

The respondents were also asked about the government tax subsidy, and whether gasoline and electricity cost adjustments influenced their purchase decision.

Of all respondents, 11 respondents answered the question about the tax subsidy. Interestingly, all these 11 respondents thought the tax subsidy did not influence their future MEV purchase intention. Seven of them thought the taxi subsidy was a very good policy, but not a very influential one. Also, gasoline price increases didn't influence their purchase decision, perhaps because all the respondents were committed MEV users. Also the 11 respondents thought that electricity price increases would not influence their usage or future purchase intentions for the following reasons:

- “Comparing the gasoline price, I prefer an electric vehicle.”
- “I don't think a rise in electricity cost will have much of an influence.”
- “The electricity price is acceptable. I can afford it.”
- “I believe the cost for using electricity for fuel is much cheaper than using gasoline. The unit price of electricity should always be cheaper than gasoline.”

Pleasure with MEVs

"Pleasure with MEVs" here means the benefits received from MEV that include vehicle performance and vehicle design. These benefits are summarized from answers to the open-ended questions asked of the respondents. About 26% of the respondents said they enjoyed the windshield design of an MEV, 21% enjoyed vehicle performance, 6% enjoyed their MEVs' small size, and 3% liked the MEV's interior design. Also, 26% of

the respondents thought their MEV is good in utility and comfort, while 18% of the respondents stated it was just a traffic mode for trips, nothing special.

"Vehicle performance" refers to the motor power, speed, and stability of the MEVs. Some respondents experience benefits from these aspects. "It is very easy to go uphill, and the motor power is very strong." "My MEV is very stable for driving. It is convenient for me to use it." "It is fast enough for me, and I don't have to pedal it, which really saves me a lot of energy and makes it easy for me to go out."

"Shield design" refers to the benefits brought by the MEV windshield, which protects MEV users from severe weather and possible crash harm. The following comments from respondents highlight these points. "My MEV provides protection from rain and wind." "I can use my MEV when it is raining, even heavily." "The MEV is fully shielded. So I am not cold on the road in the winter."

Some respondents benefited from the MEVs' small size. "It is small, convenient for parking." "It is very flexible because of the small size, but well configured."

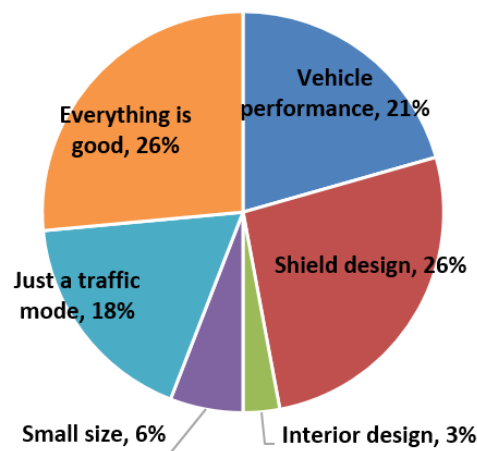


Figure 4.4. The satisfaction with MEV

The respondents were asked if there are things about the MEV that they disliked. Surprisingly, only two respondents answered this question with "yes"; one said that his MEV couldn't qualify for a legal license plate and the other said the seats of his MEV were a little hard. Most of the respondents answered "no" to the question, stating they were satisfied with their MEVs. There are several possible reasons. MEVs have met their demand for trips generally. Most respondents were old people without a driver license and thus without much driving experience with a conventional vehicle, potentially leading to their low demand for comfort and other aspects.

4.4.3 Use experience

To make better decisions about traffic policies and regulation of MEVs, it is important to understand how users use MEVs and their mode choice. The following section presents results from the survey on these issues.

Travel mode choice

Respondents were asked about their primary travel modes before purchasing an MEV. Respondents could select multiple modes. Most respondents (74%) rode e-bikes for their daily trips, while 41% used public buses, 26% bicycles, and 9% conventional vehicles, as shown in Figure 4.5. The users were also asked about any vehicles they sold after owning a MEV. Figure 4.5 indicates that 24% of respondents sold their e-bikes after purchasing an MEV, 6% sold their bicycles, and 3% sold their conventional vehicles. These results indicate that MEVs strongly replaced e-bike trips, public bus trips, and bicycle, likely as the respondents aged. MEV offered users a better alternative than cycling and public transit. Also, the result indicates that most respondents were choosing MEVs not out of economic necessity.

Trip purpose

Figure 4.6 shows primary trip purposes of the MEV respondents. . Among them, 59% of respondents used MEVs for all daily trips for different activities, indicating that MEVs were their primary travel mode. Also, 38% of the respondents used MEV mainly for trips

for recreation and exercise, 24% used them for shopping (including grocery shopping), 6% for carrying grandchildren, and 6% for general errands. Since most respondents were retired, only two respondents mentioned that they used their MEVs for commuting.

The respondents on average made trips with passengers three times per week. Thirty-two percent of respondents drove their MEVs with a passenger every day, 29% 2-3 times a week, 6% once a week, and 6% 2-3 times a month. Their passengers were their grandchildren and their spouses. About 26% of respondents drove alone or seldom with a passenger.

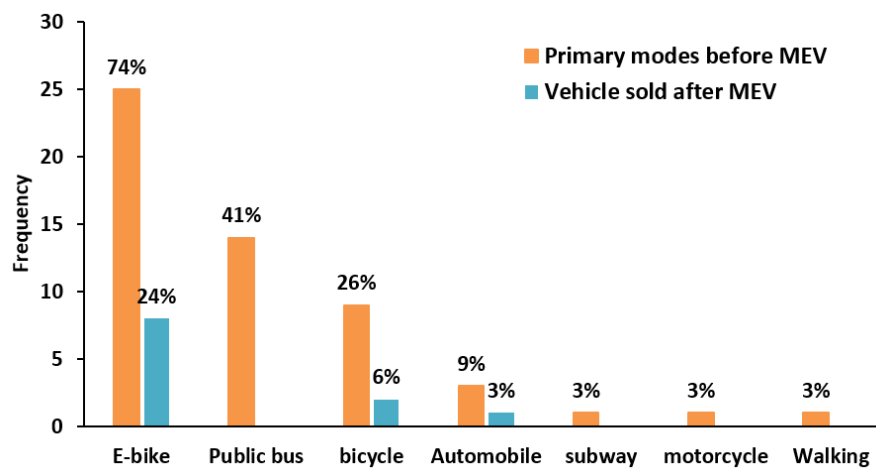


Figure 4.5. Primary modes before owning MEVs and vehicles sold after MEV purchase

Travel distance

The monthly travel distance of each respondent was calculated by ownership duration (from purchase date) and MEV mileage that was read from the odometer. The average travel distance was 488 km/month (16.3 km/day). The distribution of monthly travel distance is shown as yellow bars in Figure 4.7. About 15% of the respondents drove below 200 km/month, 27% between 201 and 400 km/month, 27% between 401 and 600 km/month, 12% between 601 and 800 km/month, 12% between 801 to 1,000 km/month, and 6% between 1,001 to 1,200 km/month.

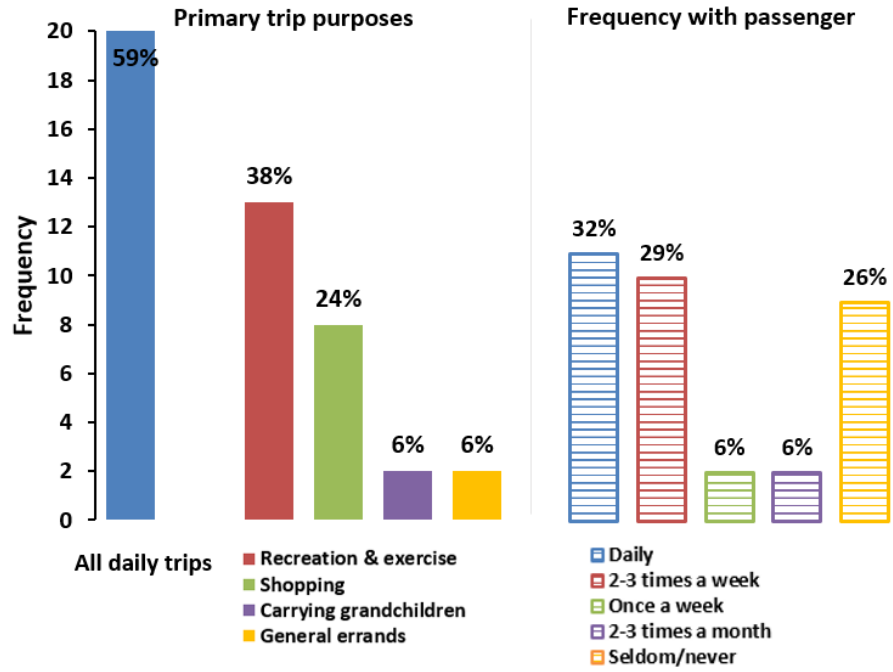


Figure 4.6. Trip purposes and trips with passenger

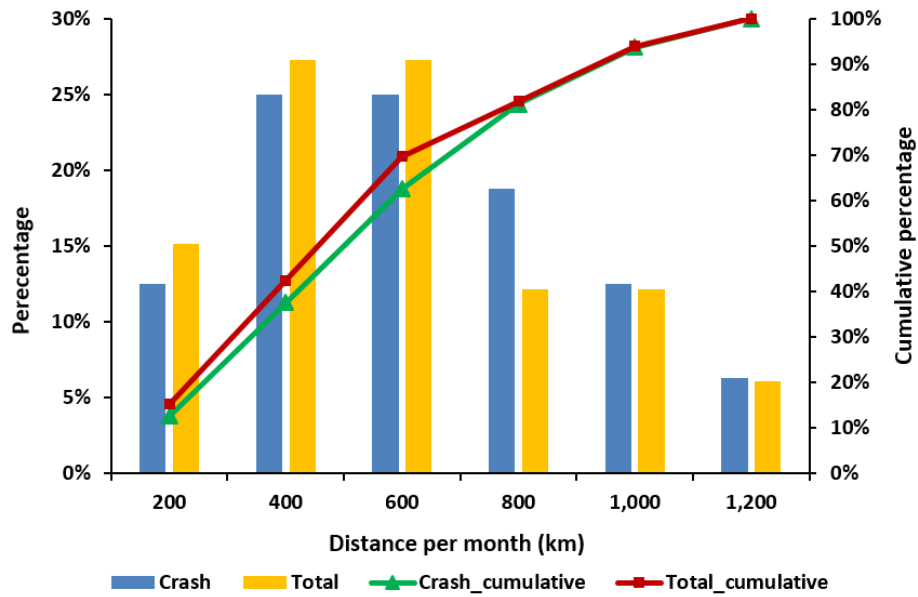


Figure 4.7. Monthly travel distance (km)

Safety perception

Figure 4.7 also shows crash information. Safety is always a serious problem in any transportation system, and new vehicle technologies prompt questions of safety. The author explored the safety issues of MEV users from two aspects, including safety perception and actual crashes. Two questions were asked in the interview: “Do you feel safe when you ride your MEV?” and “Have you had a crash with your MEV, and how severe was it?” Interestingly, all 34 respondents stated they felt very safe driving their MEVs and weren't concerned about safety issues with their MEVs. A reason mentioned by several respondents was that MEV's are slower than a conventional car. This is also consistent with previous findings, in which more than 25% of respondents stated that MEV's speed was a primary purchasing reason, and 9% had not chosen a car because of the high speed of conventional cars.

However, 16 respondents (47%) have had previous crashes, with differing injury severities. Among them, 11 respondents had crashed once with slight injuries or only minor vehicle damage. Four respondents had crashed several times. One respondent had a serious injury and stayed in the hospital for a while. As with most survey research, especially qualitative survey research, our sample may suffer from self-selection and self-reported bias (Popovich et al. 2014). For example, our sample could not cover MEV respondents who might have had serious or fatal crashes. Nevertheless, our study shows that there is a potential contradiction between respondents' perceived safety and the real rate of crashes. The safety perception was overrated, and not consistent with the real crash experiences; or that the crashes that occurred did not result in a perceived threat to the respondent. This may be because most respondents who had crash experiences did not have severe injuries; it may also be because 59% of the respondents didn't have a driver license, meaning they were not well trained or educated about traffic safety knowledge. The interview did not include questions about risk or injuries to other road users that were involved in the crashes and is an area of future investigation.

The total crash rate per 100km is 0.00259. The travel distance per month of the respondents who had crashes with their MEV are plotted in Figure 4.7. More respondents drove 601 to 1,200 km/month compared to total respondents (38% vs. 30%), while fewer respondents drove 0 to 600 km/month compared to total respondents (62% vs. 70%). This indicates more exposure with greater travel distance, and thus perhaps a higher crash possibility.

Maintenance

Because MEVs are an emerging travel mode, there is little information about vehicle performance. Respondents were asked how they performed maintenance for their MEVs and how often they had mechanical problems. About 50% of the respondents had never done any maintenance until the time of the survey; 15% performed maintenance by themselves at home, 15% did monthly maintenance at MEV dealers or repair shops, and 6% performed an annual check, as shown in Figure 4.8. Interestingly, 15% of respondents said they only performed occasional car washes, and never did any maintenance. Most respondents seldom or never had any mechanical problem with their MEVs (62% never, and 21% seldom). Only 18% of respondents said their MEVs sometimes had a problem during driving. Among these people, three respondents changed the battery for their MEVs (owning their MEVs for 21 months, 40 months, and 50 months respectively).

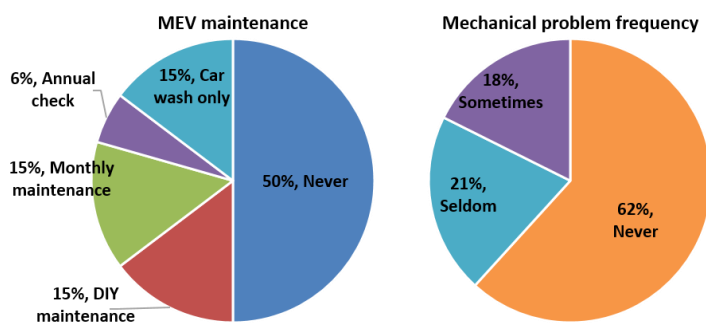


Figure 4.8. MEV maintenance and mechanical problem frequency

On-road operations

An MEV is slower and smaller than a conventional vehicle but faster than an e-bike or bicycle. MEVs lack the same level occupant protection as conventional cars, but offer more occupant protection than two-wheelers. Mixing MEVs with other vehicles could create safety challenges for MEV users or other road users. Unlike rules governing the use of Neighborhood Electric Vehicles (NEVs) in the USA, the road rules for MEV's in China are undefined and ambiguous. For the 34 respondents the author surveyed, 30 respondents (88%) drove their MEVs in motorized vehicle lanes, and 3 respondents in non-motorized vehicle lanes (bicycle and e-bike lanes). One respondent said that where they drove depended on road availability; that is, sometimes they drove in motorized vehicle lanes and sometimes in non-motorized vehicle lanes.

Parking and charging

The interview also explored parking situations for MEVs. At-home parking locations can be grouped into three categories, including roadside/outside house (9%, and 12%, respectively), bicycle parking lot (21%), and car parking lot (59%). Bicycle parking lots usually charge 30-60 RMB monthly, while car parking lots charge 50-60 RMB monthly if the parking space does not belong to the owner. For away-from-home parking, similarly, parking locations include roadside parking (71%), car parking lot (26%), and bicycle parking lot (3%).

MEV charging frequency varied, depending on battery capacity, battery performance, and trip distance. Most of the respondents charged their MEVs every two or three days (35%, and 41% respectively), 18% every day, and 6% every four days or more.

4.5 Conclusion

This paper, as far as the author is aware, provides the first detailed insight into MEV users' use experience and perceptions of MEVs. The author found that most users were male, elderly, and retired people with high household incomes. The MEVs they owned

averaged about 2.3 meters long, 1.3 meters wide, and 1.5 meters high, and mostly had 4 wheels and 3 seats; most used lead acid batteries. The average range was close to 100 km, with a maximum speed from 40 to 60 km/h. Only 41% of the respondents had a driver license. Their purchase intentions were mostly driven by mobility and accessibility (expressed as convenience by the respondents), age or physical limitation, and low cost. These respondents thought an MEV's speed was suitable for them, being lower than the speeds of conventional cars. Most of them were pleased with their vehicles' performance and well-protected design. These users had shifted from being e-bike and public transit users, showing an increasing demand for different travel modes and mobility. The results corroborate the author's previous research, which suggested that e-bikes are an intermediate mode of motorization in China (Ling et al. 2015). About 60% of the respondents relied on MEVs for their daily trips with one passenger or more frequently accompanying them, showing the important role of MEVs in their daily lives. Most respondents didn't do maintenance regularly, and only 21% of them did monthly maintenance or annual check. Their MEVs' mechanical performance was stable and reliable, and most of them seldom or never had problems. Approximately 80% of the respondents charged their MEVs every two or three days.

About half of the respondents had crash experience during the average ownership of 3 years. Surprisingly, all the respondents were never concerned about safety issues. This shows a contradiction between users' real safety situations and their perceived safety, which may result from a low percentage of driver licenses among the respondents or from most respondents' lacking correct traffic safety knowledge. Nearly 90% of the respondents drove in motorized vehicle lanes, and 59% parked in car parking lots at home. When away from home, they parked their MEVs on the roadside mostly, which means there was a certain potential for informal or illegal parking.

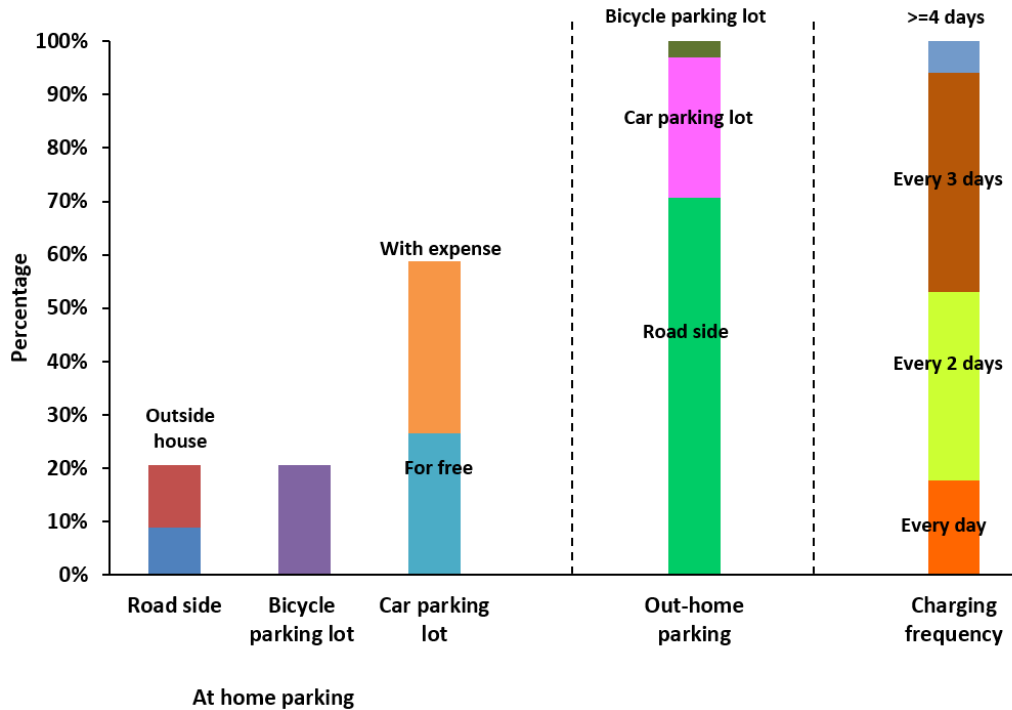


Figure 4.9. MEV parking and charging

4.5.1 Implications for policy and recommendations

“If we make electric cars in the exact same way we’ve made cars for the last hundred years – big steel frame structure, remove the combustion engine and replace it with an oversized and overpowered electric powertrain – that’s problematic” (Jefferies 2017). According to the results, an MEV is a very clean-energy traffic mode with high mobility and accessibility and reliable performance. Some measures are made based on the study’s result, which may improve current MEV use pattern in China. The current MEV market caters almost exclusively toward elderly populations, and without some specific policy or marketing interventions, the image of MEVs will not penetrate large numbers young people, despite the promise of low-cost and relatively clean personal mobility.

MEV standard

I propose to create new standards for MEVs, considering vehicle size, style, maximum speed, battery, safety performance and other aspects. With an MEV standard, the initial MEV market may be boosted in a reasonable, and healthy way. Also, in the background of promoting new energy vehicles, having an MEV standard may play an important role in balancing people's increasing personal/household demand for car ownership with a low-cost alternative that will assist with national energy and environment issues.

License system

Licensing MEVs would make it easier to control the MEV population and to regulate users. MEVs should be required to register and have a license plate. Also users should have a driver license so that they can get traffic safety education and be well trained to drive on the roads. Some respondents in the study stated that they couldn't get a driver license because of age limitations and physical limitations. A special driver license and with expanded age limitation is suggested to meet the aging population's travel demands.

Regulation and insurance

I recommend to enhance traffic management to reduce reckless MEV driving and increase all road users' awareness of MEVs. MEVs should be prohibited from using expressways or main road systems because of their low speeds. A low-speed road network should be developed and maintained for MEVs and the safety of all road users. A map navigation system considering road-speed limitation can aid drivers, as more and more vehicles (conventional vehicles and MEVs) are equipped with GPS systems. Traffic laws and insurance requirements should be imposed to improve safety and accident management.

MEVs' future

Currently, MEVs are gaining popularity among older people. However, MEVs can also be a reliable mode for people living in suburbs and rural areas who have an increasing desire for car travel but prefer to a low-cost mode. Also, MEVs can be a good choice for young people who are living in high-density urban areas because of the advantages of parking flexibility, low cost, and small size. Also, many respondents have noticed the cheap charging fee for MEVs. This is a good feature for promoting new energy vehicles and could help establish a positive image for them. According to previous studies, social networks, especially family members and friends, could play an important role in the adoption of new technology vehicles (Popovich et al. 2014, Rezvani et al. 2015). Current MEV experience may encourage household car purchase inclination to move toward new energy vehicles in the future. Also, MEVs can contribute to a vehicle-sharing system to cover “last mile” trips with small vehicles operating at low cost and with low emissions compared to conventional cars; they can also deal with bad weather, and avoid the sweat, effort, and other problems with bike-sharing systems.

4.5.2 Limitations and future research

The major limitation of the paper is the limited sample size. In particular, the author was not able to assess the driving behavior, mode shift, and new trip generation among MEV users in a quantitative way. Greater sample sizes from other areas and with other age groups could allow us to broaden our study to interactions with other road users and infrastructure. However, this study constitutes only the first glimpse into MEV users and their use experience and perception. The increase in MEV ownership will have an influence on road capacity, but that influence is not clear. Also, the environmental influence and energy efficiency of MEVs are not fully understood. Future studies should carefully evaluate MEVs' positive and negative effects on the environment in terms of life-cycle assessment.

CHAPTER 5
BEHAVIORAL LIFE CYCLE ASSESSMENT

Abstract

Current Life Cycle Assessment (LCA) models have evolved from technology-oriented attributional models that focus heavily on production processes and seek to allocate broader economy-wide environmental impacts to those processes. In this study, a new approach named Behavioral Life Cycle Assessment (BLCA), one including explicit, probability-based behavioral inputs that influence choices in the LCA process, is developed. A case study is conducted using the BLCA framework to compare the environmental impacts of alternative fuel vehicle choice behavior under nine different scenarios considering policy, technology, charging infrastructure, recharging time, and other attributes. The results indicate that purchase incentives for alternative fuel vehicles influence purchase intentions and ultimately lead to relatively low energy consumption and the lowest CO₂ emission among the nine posited scenarios. An LCA model is built for evaluating energy consumption, greenhouse gas, and pollution emissions of life cycle assessment of Vehicle ownership and usage based on China's national conditions. A case study using China's LCA model and considering traffic restrictions on gasoline vehicles is evaluated. For daily trips, driving alone in a gasoline vehicle consumes the most energy, while micro electric vehicles (MEVs) consume the least. Driving alone in an electric vehicle (EV) generates the highest SO₂ emissions compared to driving a gasoline car alone, carpooling in a gasoline-powered car with four people, and driving a micro electric vehicle.

5.1 Introduction

Accurately estimating energy and environmental impacts from products or processes is an increasingly critical task in policy development, particularly as environmental impacts become more explicitly monetized in the market (e.g., through ecolabeling) or in regulatory frameworks (e.g., in carbon regulation). Life cycle assessment (LCA) is the assessment of the environmental impact of a product or service throughout its life cycle (Klöpffer 1997, Baumann et al. 2004). Environmental LCA is an evolving field that has

become a mainstream environmental accounting method in the past two decades (Finnveden et al. 2009).

Current LCA models have evolved from technology-oriented attributional models that focus heavily on production processes and seek to allocate responsibility for broader economy-wide environmental impacts to those processes. However, challenges with marginal effects, system boundaries, impact allocation, data resolution, and policy impacts have prompted the development of consequential LCA models to control for secondary effects of industry-level decision-making. Traditional LCA methods have not explicitly considered or modeled the behavioral choices of consumers during either the use or waste management phases of a product, or the behavioral choices of companies during the material acquisition or manufacturing phases. For many products or processes, the attributes of the product do not change the way it is consumed (e.g., gasoline vs. ethanol fuels for vehicles). However, some products have intrinsic characteristics that change the way they are consumed (e.g., conventional vs. plug-in electric drive vehicles). The way one uses a product can have a large impact on its environmental intensity. For electric vehicles, it is possible to have near-zero use-phase emissions under some circumstances, depending on the technology and recharge behavior of the user. In the case of plug-in hybrid electric vehicles, the use-phase emissions can vary widely depending on the distance traveled, whether powered by gasoline or electricity, all related to recharge behavior.

In this study, a new approach named Behavioral Life Cycle Assessment (BLCA) is developed to include explicit, probability-based behavioral inputs that influence choices in the LCA process. BLCA builds on traditional approaches to LCA and follows a similar motivation to that of consequential LCA, but includes decision-making process to make it more powerful. A case study is conducted using the BLCA framework to compare the environmental impacts of conventional vehicles (CVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs) while considering choice behavior.

In addition, a China-oriented LCA database is built for the purpose of evaluating how energy consumption, greenhouse gas emissions, and other polluting emissions impact the life-cycle assessment of vehicle ownership and usage for China; the evaluation includes manufacturing and uses two major stages. This is the first China-oriented LCA model for a transportation system, to the author's knowledge.

The remainder of the paper is organized as follows: the Literature Review introduces previous LCA models in the area of transportation. The Behavioral Life Cycle Assessment Model presents the model's framework, explains the model's implementation, and presents a case study of the influence of electric vehicle choice on the environment using the BLCA model. The section Life Cycle Assessment Model for the Transportation System in China presents an LCA model for vehicles in China. The Conclusion summarizes the results, limitations, and future work of the study.

5.2 Literature Review

LCA techniques are used to evaluate the environmental effects of a product or service system through all stages of its life-cycle, providing an adequate instrument to support environmental decision-making. Various studies have used LCA techniques to evaluate the environmental impact of different vehicles (Samaras et al. 2008, Ou et al. 2010c, Ou et al. 2013, Bauer et al. 2015, Noshadravan et al. 2015). The Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) model developed at Argonne National Laboratory is mostly used for analysis in the U.S, and it evaluates energy and greenhouse gases and pollution emissions' impacts; it also enables life-cycle analysis of multiple transportation fuels and various transportation modes. (Wang 2008, Nealer et al. 2015). This model was developed as a spreadsheet-based model and has recently transitioned to a web-based interface. Some studies have focused on scenarios with reduced travel or incorporation of new modes of travel to reduce energy consumption and CO₂ emissions, finding that a 20% reduction in energy use and CO₂ (compared to baseline) is achieved just from the transport sector if car and air travels are reduced by 25% by year 2050 around the world (Cuenot et al. 2012). The Oak

Ridge National Laboratory's Market Acceptance of Advanced Automotive Technologies (MA³T) Model (shown in Figure 5.1) is also widely used in the U.S. to simulate market demand for advanced vehicle technologies by representing relevant attributes of technologies and consumer behavior and predefined market conditions (Chapin et al. 2013, Manley et al. 2014, Transportation Energy Evolution Modeling 2017). On a macro level, the VISION model provides estimates of potential energy use, oil use, and carbon emissions impacts of highway vehicles up to the year 2100 and was developed by the Argonne National Laboratory of the US Department of Energy (Zhou et al. 2014).

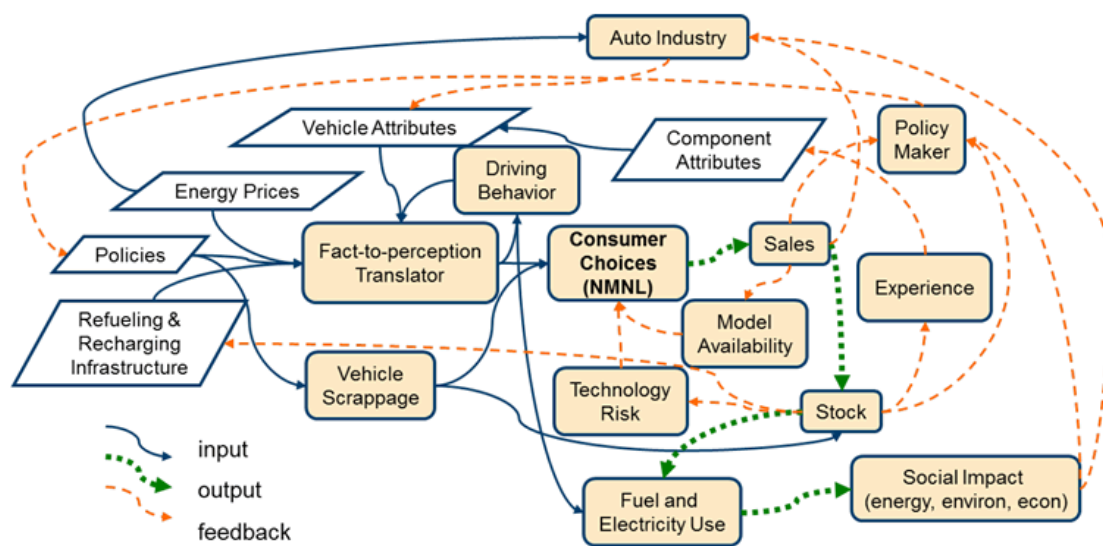


Figure 5.1. MA3T model (source from Transportation Energy Evolution Modeling (2017))

Some researchers have focused on the Chinese market (Ou et al. 2010c, Huo et al. 2015). Tsinghua_CA3EM (China Automotive Energy, Environment, and Economy) model is an integrated model for China's automotive energy supply-and-demand balance calculation; it is based on the GREET model as well as China's national conditions (Ou et al. 2009, Ou et al. 2010b). In addition, a Chinese transportation energy model has been developed to first estimate the market share captured by each transportation mode and then to use the Global Change Assessment Model (GCAM) to estimate long-term energy consumption and CO₂ emissions for various policy cases (Yin et al. 2015). That study

showed that final energy consumption decreases by approximately half by year 2095, when passenger and freight energy consumption will decline by 41% and 56%, respectively, from the reference scenario in which carbon policy is implemented (Yin et al. 2015). In the US, a report studied various strategies beyond technology and infrastructure advances for achieving 50 percent GHG emission reductions relative to 2005 in the transportation sector by 2050, using the VISION model (Cazalot Jr et al. 2012).

With the development of alternative vehicles, especially electric vehicles, many life-cycle studies of hybrid and electric vehicles have been conducted. Hawkins et al. (2012) reviewed 51 life-cycle studies of hybrid and electric vehicles, finding that CO₂ emissions were reported by most studies with different scope and methods. A study conducted by the U.S. Department of Energy compared the cradle-to-grave lifecycle GHG emissions of EVs and found that HEVs, PHEVs, and shorter-range BEVs had lower GHG emissions compared to conventional gasoline vehicles on average (Joseck et al. 2014). Hawkins et al. (2013) found that EV use results in fewer GHG emissions than gasoline vehicles, using process level energy and GHG emissions data (Nealer et al. 2015). They also found that EVs may result in higher eco-toxicity than gasoline vehicles. In a study focusing on light-duty battery electric vehicles, the researchers found that 18.5% of energy consumption and 17% of GHG emissions came from the production of EVs and the rest, 81.5% and 83%, respectively, came from the vehicles' use (Shen et al. 2015).

Though LCA methods are widely used, they are imperfect in many ways, particularly related to system boundary issues between the technical system and the environment, impact allocation, temporal resolution and horizon, and data availability (Lundie et al. 2007). Many of the research contributions in the past decade have attempted to simplify accounting complexities between environmental relationships throughout industries (Hendrickson et al. 1998). Current Life Cycle Assessment (LCA) models have evolved from technology-oriented attributional models that focus heavily on production processes and seek to allocate broader economy-wide environmental impacts to those processes.

However, how a consumer uses a product may have a substantial impact on the life cycle of that technology. Emerging technologies in the transportation sector stand out as examples of intrinsic characteristics of the technology changing the way a product is used, ultimately affecting environmental emissions and health.

5.3 Behavioral Life Cycle Assessment Model

5.3.1 Framework

In concept, the general proposed conceptual framework for BLCA is shown in Figure 5.2. The right side of the figure describes a general LCA framework, focusing on four key phases of a product's lifecycle (raw material acquisition, manufacturing, use, and waste management). The technological system boundary requires inputs of raw materials, energy and other inputs, and the outputs include co-products, waste products, emissions (GHG and local emissions), and toxic releases, all of which ultimately lead to environmental and health damages. The left side of the figure is the decision system. The decision system is a probability-based choice framework. This decision system takes, as inputs, attributes of technology (e.g., vehicle recharge times, product materials, etc.), individual or firm specific attributes (e.g., demographics; firm size, corporate environmental philosophy), and economic and policy attributes (e.g., taxes, fiscal incentives, production prices). The output of this decision system is the probability of choosing an alternative out of a set of choices. This behavioral approach could be applied to some or all of the four phases of the product life cycle. The main data inputs for the decision system of BLCA are existing (revealed) industrial firm response data and consumer demand response data. In the transportation sector, compatible choice data are generally collected in regular household travel surveys.

Also, the behavioral model is flexible, and can be a vehicle choice model, a trip choice model, or other models such as customer purchase decision models which are not limited to the transportation area. Thus, the BLCA model is a flexible and automatic model to evaluate alternative inputs' sensitivities of energy consumption and emission. The BLCA

model is different from current LCA models in the transportation area since the BLCA model is not only used for evaluating alternative fuel change behavior's influence on the environment, but also can be employed to evaluate trip mode shift behavior too. For example, using the BLCA model, energy consumption and pollution emission can be estimated if emerging technologies (e.g. e-bikes) cause dramatic shifts in mode split, as they have in China.

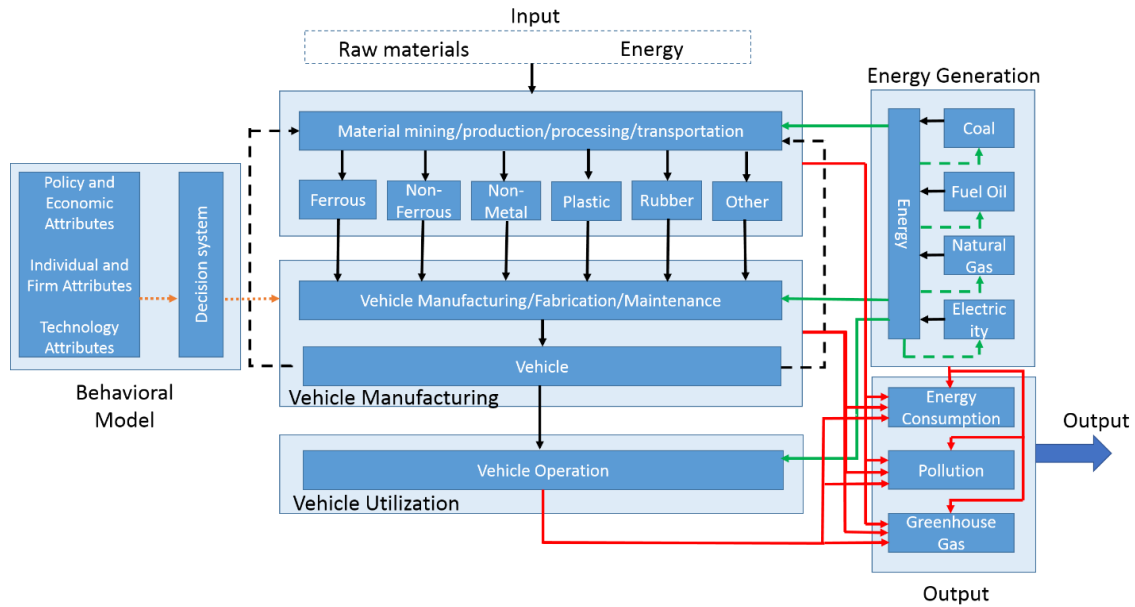


Figure 5.2. Behavioral LCA (BLCA) system framework

5.3.2 Case study of BLCA framework

The BLCA adopts a multivariate causal framework for decision-making. Decisions are a function of multiple observable attributes that describe technology, firms or individuals, and policy or economic conditions. A case study is conducted to show how the BLCA framework works. In the case study, the objective is to evaluate the influence of technology changes, policy promotions, and refuel system development's influence on vehicle purchase behavior, then to evaluate the influence of the vehicle LCA energy consumption and emission. For the decision system, a discrete choice model of consumer

preferences for alternative fuel vehicles conducted by Hackbarth et al. (2013) was chosen. The GREET model, which has been widely used by many of the vehicle LCA studies and is publicly available is used to estimate the energy consumption and GHG emissions.

The sample was drawn online, with the restriction that potential respondents should have purchased their last vehicle within one year, or plan to purchase a new car within the next year. The stated preference discrete choice experiment was used to survey respondents purchase intention of seven fuel types including conventional vehicles (CV), natural gas vehicle (NGV), hybrid electric vehicle (HEV), plug-in electric vehicle (PHEV), battery electric vehicle (BEV), biofuel vehicle (BV), and hydrogen fuel cell vehicle (FCEV). A mixed (error components) logit (MXL) model is used in the Hackbarth et al. (2013) study. The probability that the person n makes a specific purchase choice $i = i_1, \dots, i_T$ is given by

$$Un_j = \beta' x_{nj} + u'_n z_{nj} + \varepsilon_{nj}$$

$$P_{ni} = \int_{u_{n1}} \dots \int_{u_{nK}} \prod_{t=1}^T \frac{\exp(\beta' x_{nit} + \sum_{k=1}^K u_{nk} d_{jk})}{\exp(\beta' x_{njt} + \sum_{k=1}^K u_{nk} d_{jk})} \phi(u_{n1}|0, \sigma_1) \dots \phi(u_{nK}|0, \sigma_K) du_{n1} \dots du_{nK}$$

where $\beta' x_{nj}$ is the deterministic part of utility, x_{nj} is a vector of observed attributes and policy attribute of the vehicle alternative j , and socio-demographic characteristics and household characteristics of the respondent n , and β' is a vector of unknown fixed parameters. $u'_n z_{nj} + \varepsilon_{nj}$ represents the stochastic portion of the utility, with z_{nj} being a vector of observed attributes relating to alternative j . The term u'_n is a random vector with zero mean, and ε_{nj} is a random term which is independent and identically Gumbel distributed. In the model conducted by Hackbarth et al. (2013), the vehicle alternatives are grouped into K nests. So z_{nj} is defined as a vector of dummy variables d_{jk} . The error components is

$$u'_n z_{nj} = \sum_{k=1}^K u_{nk} d_{jk}$$

where u_{nk} is a random variable, as the utility functions.

Nine scenarios were simulated by Hackbarth et al. (2013), as shown in Table 5.1.

The GREET model is used to assess vehicle life cycle and well to wheel energy consumption and emissions. Using the BLCA model, the influences of policy, vehicle technology, and charging infrastructure on energy consumption, and emissions over the life cycle is evaluated. Mileage of all types of vehicles was assumed at 125,000 miles. In the case study, only CV, HEV, PHEV, and BEV were considered. The other vehicles are excluded from the LCA part. Total energy consumption and CO₂ emission are estimated to the scenarios, assuming 1,000 vehicles total.

Table 5.1. Mode choice shares of the vehicle technologies in the scenarios (in %).

Scenario	CV	HEV	PHEV	BEV	Other
1: Base case	30.35	20.08	10.85	2.24	36.48
2: Incentives for PHEVs, BEVs, BVs, FCEVs	27.01	17.34	13.83	2.26	39.56
3: Purchase discount for PHEVs, BEVs, FCEVs	28.89	18.79	12.23	3.02	37.07
4: Purchase price of \$ 25,362 for all vehicles	23.14	20.6	14.38	4.86	37.02
5: Battery leasing contract for BEVs of \$ 93 /month, purchase discount for BEVs	30.19	19.92	10.77	2.83	36.29
6: 750 km driving range for BEVs	29.58	19.21	10.34	5.45	35.42
7: 100% fuel availability for all AFVs	25.74	16.87	11.73	2.77	42.89
8: Battery recharging time of 5 min	29.79	19.45	11.75	3.28	35.73
9: Combination of Scenarios 2, 3, 7, and 8	21.39	13.03	18.08	5.47	42.03
Note: Other: (NGV+BV+FCEV); The table is adapted and revised from (Hackbarth et al. 2013)					

As Figure 5.3 shows, scenario 7 would consume the least energy in the vehicle life cycle, partly because other type of vehicles were excluded from the total energy consumption evaluation due to data availability. PHEV and BEV's total energy consumption is very

sensitive to the behavior related attributes. The Scenario 2 has the least CO₂ emission among all the scenarios, while Scenario 6 has the highest CO₂ emission, as shown in Figure 5.4. CO₂ emission to the scenarios. The large driving range for BEVs seems reduce respondents' range anxiety, and encourages more people to choose BEV, which results in high relative change of CO₂ emission compared to the base case scenario.

The BLCA model is different from conventional LCA model since the BLCA model can evaluate kinds of policies and technology changes' influence on the environment emission and energy consumption directly. Furthermore, the BLCA model allows policy makers test any combination of possible attributes and calculate LCA output, and compare that to other combination as needed. Thus, the BLCA model would be very helpful with testing new technology, possible infrastructure development, future policies, and other attributes' influence on the environmental output directly, and help policy makers make effective and environment-friendly decisions.

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5.4 Life Cycle Assessment Model for Transportation System in China

An Excel-based China LCA database was developed to evaluate the impact of vehicles and use life-cycle on the environment in China. China's transportation system relies heavily on domestic manufacturing and energy supply and thus motivates the development of a China-oriented LCA.

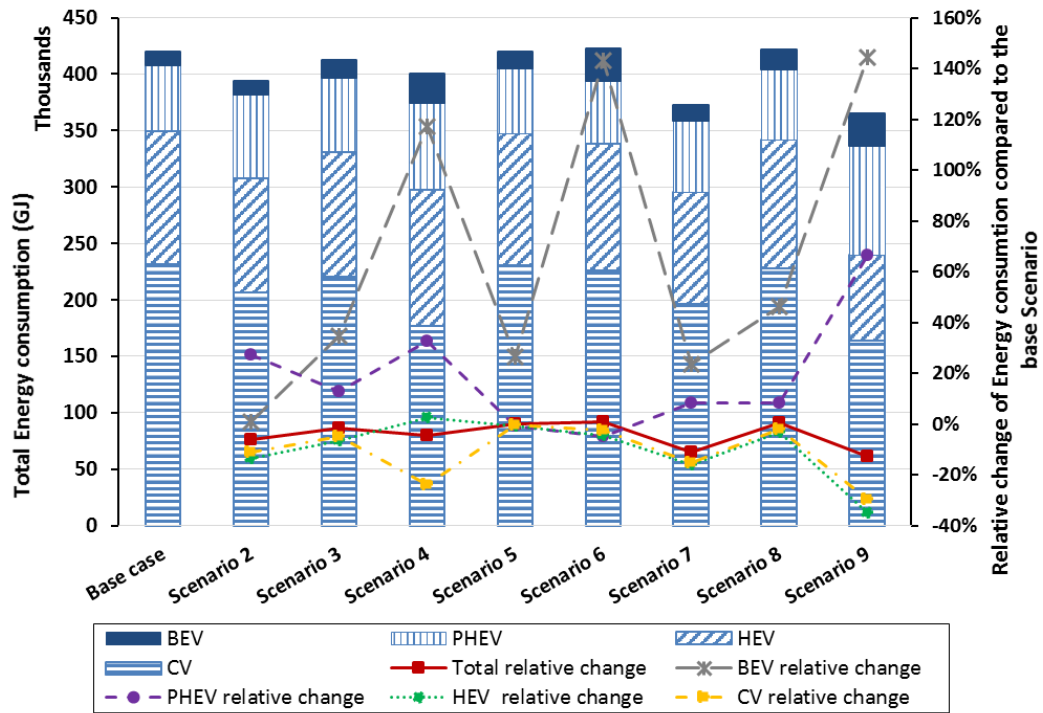


Figure 5.3. Total energy consumption to the scenarios, and relative change compared to the base scenario

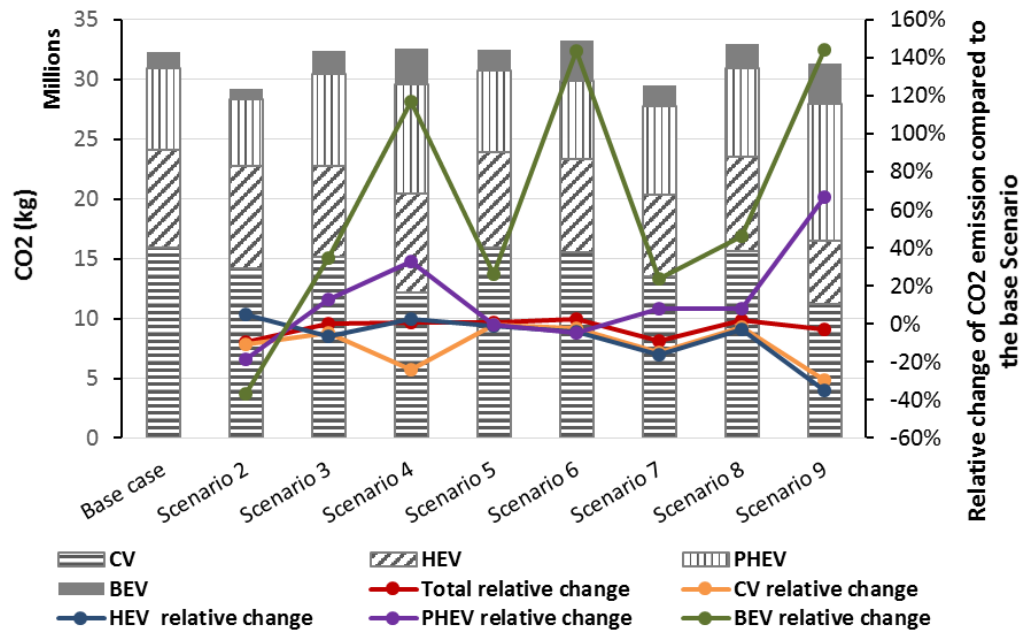


Figure 5.4. CO2 emission to the scenarios

5.4.1 Data collection

There are three major stages in the LCA including manufacturing, use, and end of life. In this dissertation, the manufacturing and use stages are the focuses. Data categories include production values, energy consumption, water pollution, air pollution, and solid waste pollution. Data were collected from the following official public data sources:

- IBISWorld
- China Statistical Yearbook 2011 (data from 2009-2010)
- China Statistical Yearbook 2015 (data from 2013-2014)
- China Data Online
- China Energy Databook
- Association of Natural Rubber Producing Countries.

5.4.2 China life cycle assessment model

Abbreviations include the following:

i: type index of aggregated material used to manufacture the vehicle (ferrous, non-ferrous, non-metal, etc.);

j: the index of procedure to obtain the material (mining, smelting, processing, etc.);

k: type index of fuel used to produce material or other energy source (coal, coke, crude oil, natural gas, electricity, etc.),

l: type of pollution generated during manufacturing or vehicle usage (industrial waste water, sulfur dioxide, industrial soot, etc.);

m: type of vehicle fuel (gasoline, diesel, electricity, etc.).

5.4.2.1 Total Energy

Total energy includes the energy used to manufacture the vehicle and the energy used by the car for operation, i.e. well-to-wheel energy:

$$E_{TOTAL} = E_{MF} + E_{WTW}$$

where E_{TOTAL} is the total energy, E_{MF} is the energy used in manufacturing, and E_{WTW} is the well-to-wheel energy.

E_{MF} is the sum of the energy used to manufacture each type of material i , denoted by E_i .

E_i further includes j manufacturing procedures, and in each procedure, the energy includes energy directly used to obtain material i , and the energy indirectly used to generate the fuels used in manufacturing:

$$E_{MF} = \sum_i E_i = \sum_i \sum_j (EM_{i,j} + EE_{i,j})$$

Here $EM_{i,j}$ is the energy used to obtain material i in procedure j , and $EE_{i,j}$ is the energy consumed indirectly to generate the fuel used for $EM_{i,j}$.

$EM_{i,j}$ is calculated by the energy used per unit and the total amount of material i in each vehicle:

$$EM_{i,j} = C_{i,j}m_i = C_{i,j}m_{car}p_i$$

where $C_{i,j}$ is the energy intensity (GJ/kg) of material i in procedure j ; m_i is the weight of material i finally obtained after all procedures; m_{car} is the weight of the car; and p_i is the weight percentage of material i in car.

The energy intensity $C_{i,j}$ is calculated by the ratio between the total energy used ($E_{i,j}$) and the total weight of material i finally obtained ($M_{i,j}$) according to annual nationwide data.

$$C_{i,j} = \frac{E_{i,j}}{M_{i,j}}$$

$EE_{i,j}$ is calculated by each type of fuel used:

$$EE_{i,j} = \sum_k C_k m_{i,j,k}$$

where C_k is the energy intensity (GJ/kg or GJ/kWh) of fuel k ; $m_{i,j,k}$ the amount of fuel k (kg or kWh) used to produce material i in the procedure j .

The energy index C_k is calculated by the ratio between the total energy used (E_k) and the total weight of material i finally obtained (M_k) according to the annual national-wide data.

$$C_k = \frac{E_k}{M_k}$$

The well-to-wheel energy (E_{WTW}) equals the sum of well-to-pump energy (E_{WTP}) and pump-to-wheel energy (E_{PTW}).

$$E_{WTW} = E_{WTP} + E_{PTW}$$

E_{WTP} can be calculated by the manufacturing energy for vehicle fuel per unit and the amount of vehicle fuel used:

$$E_{WTP} = C_m m_m$$

where C_m is the energy intensity (GJ/kg) of vehicle fuel i , calculated in the same way as C_k ; and m_m is the weight (kg) of vehicle fuel m consumed by vehicle in a specified operation time period.

For gasoline cars, E_{PTW} can be calculated by

$$E_{PTW} = SE_m \cdot m_m$$

SE_m is the specific energy (GJ/kg) of the vehicle fuel m .

For EVs, E_{PTW} can be calculated by

$$E_{PTW} = \frac{E_{USE}}{\eta_{Chr}}$$

Where E_{USE} is the electricity (kWh) consumed by an EV in the specified operation time period, and η_{Chr} is the charging efficiency of the EV.

5.4.2.2 Air and water emissions

Emissions in vehicle LC are calculated by different pollution type l . For each type, the total pollution includes the vehicle manufacturing stage and the WTW stage:

$$P_{TOTAL,l} = P_{MF,l} + P_{WTW,l}$$

where l is the type of aggregated pollution (industrial waste water, sulfur dioxide, industrial soot, etc.); $P_{TOTAL,l}$ is the total amount of pollution l , $P_{MF,l}$ is the pollution l generation in vehicle manufacturing, and $P_{WTW,l}$ is the pollution l generated in well-to-wheel procedure.

$P_{MF,l}$ is the sum of the pollution expelled by manufacturing each type of material i , denoted by $P_{l,i}$. $P_{l,i}$ further including j manufacturing procedures, and in each procedure, the pollution includes pollution directly expelled in obtaining material i , as well as the energy indirectly used to generate the fuels used in manufacturing:

$$P_{MF,l} = \sum_i P_{l,i} = \sum_i \sum_j (PM_{l,i,j} + PE_{l,i,j})$$

where $P_{l,i}$ is the pollution l generated while manufacturing material i ; $PM_{l,i,j}$ is the pollution l generated to obtain material i in procedure j , and $PE_{l,i,j}$ is the pollution l generated by the fuel indirectly consumed in generating energy $EM_{i,j}$.

$PM_{l,i,j}$ is calculated by pollution intensity and the amount of corresponding material:

$$PM_{l,i,j} = PC_{l,i,j}m_i = PC_{l,i,j}m_{car}p_i$$

where $PC_{l,i,j}$ is the pollution intensity (kg pollution/kg material) of pollution l in manufacturing material i in procedure j .

The pollution intensity $PC_{l,i,j}$ is calculated by the ratio between the total pollution $P_{l,i,j}$ and the total weight of material j finally obtained $M_{i,j}$ according to annual nationwide data:

$$PC_{l,i,j} = \frac{P_{l,i,j}}{M_{i,j}}$$

$PE_{l,i,j}$ is calculated by:

$$PE_{l,i,j} = \sum_k PC_{l,k} m_{i,j,k}$$

where $PC_{l,k}$ is the pollution intensity (kg pollution/kg fuel) of fuel k .

The pollution intensity $PC_{l,k}$ is calculated by the ratio between the pollution l generated ($P_{l,k}$) and the total weight of fuel k finally obtained (M_k) according to the annual nationwide data.

$$PC_{l,k} = \frac{P_{l,k}}{M_k}$$

The type l well-to-wheel pollution ($P_{WTW,l}$) equals to the sum of well-to-pump pollution ($E_{WTP,l}$) and pump-to-wheel pollution ($P_{PTW,l}$):

$$P_{WTW,l} = P_{WTP,l} + P_{PTW,l}$$

$P_{WTP,l}$ can be calculated by:

$$P_{WTP,l} = \sum_k PC_{l,k} m_k$$

where k is the fuel type (gasoline, electricity, diesel, etc.).

For gasoline cars $PC_{PTW,l}$ can be calculated by:

$$PC_{PTW,l} = PGI_{l,m} \cdot m_m$$

$PGI_{l,m}$ is the pollution intensity (kg pollution/kg vehicle fuel) indicating the weight of pollution l generated by consuming vehicle fuel, and m_m is the weight of the vehicle fuel used in a specified operation time period.

For EV, $P_{PTW,l}$ is assumed to be 0 for any pollution l , but any pollution may be added to the model as necessary.

5.4.2.3 Greenhouse Gas (GHG)

Different types of GHG can be calculated using the same method. Here the carbon dioxide (CO₂) is used as an example to demonstrate the GHG emission model. Specifically, as GHG are generally sourced from fuels, the amount of GHG from each fuel is calculated separately. This will provide more information to optimize the energy structure.

Similar to total energy and pollution, GHG emissions from each fuel k are the sum of GHG emissions from manufacturing and WTW:

$$GHG_{total} = \sum_k GHG_{total,k} = \sum_k (GHG_{MF,k} + GHG_{WTW,k})$$

where GHG_{total} is the total GHG emission (kg), k is the fuel type; $GHG_{total,k}$ is the total GHG from fuel k ; $GHG_{MF,k}$ is the GHG emission from fuel k in vehicle manufacturing; and $GHG_{WTW,k}$ is the WTW GHG emission from fuel k .

$GHG_{MF,k}$ is the sum of GHG emission in each material production:

$$GHG_{MF,k} = \sum_i GHG_{k,i} = \sum_i \sum_j (GHGM_{k,i,j} + GHGE_{k,i,j})$$

where i is the type of aggregated material (ferrous, non-ferrous, non-metal, etc.); $GHG_{k,i}$ is the GHG emission from fuel k generated during manufacturing material i ; j is the procedure to obtain the material, e.g., mining, smelting, processing; $GHGM_{k,i,j}$ is the GHG emission from fuel k generated to obtain material i in procedure j ; and $GHGE_{k,i,j}$ is the GHG emission from fuel k generated to produce the energy consumed in producing material i in procedure j .

$GHGM_{k,i,j}$ is calculated by GHG emission intensity and weight of the fuel:

$$GHGM_{k,i,j} = GHGC_k \cdot m_{i,j,k}$$

where $GHGC_k$ is the GHG emission intensity (kg CO₂/kg fuel) of fuel k ; m_i is the weight of fuel k directly used to produce material i in procedure j .

$GHGE_{k,i,j}$ is calculated by GHG emission intensity and weight of fuel:

$$GHGE_{k,i,j} = GHGC_k \cdot me_{k,i,j}$$

where $GHGC_k$ is the GHG emission intensity (kg CO₂/kg fuel) of fuel k ; $me_{k,i,j}$, the weight of fuel k used to produce all fuels directly used to fabricate material i in the procedure j .

The WTW GHG emission from fuel k includes two parts: WTP GHG ($GHG_{WTP,k}$) and PTW GHG ($GHG_{PTW,k}$):

$$GHG_{WTW,k} = GHG_{WTP,k} + GHG_{PTW,k}$$

$GHG_{WTP,k}$ can be calculated by:

$$GHG_{WTP,k} = GHGC_k \cdot m_{WTP,k}$$

Where $m_{WTP,k}$ is the amount of fuel k used in WTP process, and can be calculated by:

$$m_{WTP,k} = C_{m,k} \cdot m_m$$

where m is the type of vehicle fuel (gasoline, diesel, electricity, etc.); $C_{m,k}$ (kg/kg or kg/kWh) is the vehicle fuel intensity, indicating the weight of fuel k used to generate one unit generate vehicle fuel; and m_m (kg or kWh) is the amount of vehicle fuel m used in a specified time period.

For gasoline cars, $GHG_{PTW,k}$ can be calculated by:

$$GHG_{PTW,k} = GHGC_m \cdot m_m$$

$GHGC_m$ is the GHG emission intensity (kg/kg or kg/kWh) indicating the weight of GHG generated by consuming vehicle fuel m . For EV, $GHGC_m = 0$.

5.4.2.4 Data and Assumptions

5.4.2.5 Vehicle Related Data

The following data related to vehicle manufacturing and operation are used in all the calculations: total energy, pollution, and GHG emission. They are listed in this subsection.

5.4.2.6 Vehicle Manufacturing

Weight of vehicle from GREET

Material composition (% by weight)

5.4.2.7 Vehicle Operation

Annual Mileage (default: 16900 km or user input)

Fuel efficiency (gasoline: 25 mpg)

Gasoline density: 2.83 kg/gallon

5.4.3 Case study of China LCA model

Policies and technology affect trip mode choices and ultimately environmental impacts. Using BLCA model with the China LCA model developed in the study, four trip choice behaviors are evaluated in terms of emissions and energy use, including driving alone in a gasoline vehicle, driving alone in an BEV, Uber or Didi (car pool of 4 people), and driving alone in an MEV.

The vehicle materials composition of CVs and BEVs are aggregated from vehicle material compositions of GREET, which is a widely used LCA model. In Chapter 4, we found that 7 MEVs use a lithium ion battery, and 21 MEVs use a lead-acid battery. According to current new energy vehicle promotion policy, lead-acid batteries will be prohibited for future vehicle. After checking MEV material inventory from several brands of MEV manufacturers' websites and vehicle manuals, I assumed that MEV follows the materials composition of BEV, but with a lighter weight as 500 kg. Table 5.2 shows the materials composition of CVs, BEVs, and MEVs. The lifetime mileage of CVs and BEVs is assumed at 200,000 km (Hawkins et al. 2012), while that of MEVs is assumed at 75,000 km. The output of manufacturing and use is evaluated in unit per km. In the use stage, the CV's fuel economy is assumed at 10.6 kml (25 mpg), the BEV's at

18.6kWh/100 km (30 kWh/100 miles), and the MEV's at 6.25 kWh/100 km based on the estimation in the Chapter 4. The charging efficiency is assumed at 80%.

Table 5.2. Materials composition of vehicles

	CV	BEV	MEV
Non-ferrous Metals	9%	11%	11%
Ferrous Metals	73%	68%	68%
Non-Metals	3%	3%	3%
Plastics	11%	12%	12%
Rubber	2%	2%	2%
Others	2%	3%	3%
Weight of Vehicle(kg)	1293	1692	500

Here, a detailed trip choice model is not included in the following case study. The four trip choice behaviors are the possible alternatives. If a gasoline vehicle is banned on the road because of traffic restriction or other reasons, the life-cycle assessment of other modes' usage is evaluated respectively. The total energy consumption is shown in Figure 5.5. Driving alone in a gasoline vehicle has the highest energy consumption, especially in the use stage, while MEV has the lowest one. A carpool of four people has the lowest GHG emission among four trip choices, as shown in Figure 5.6. Though EVs are thought of as a clean transportation mode, the results showed that an EV has the highest SO₂ emission compared to the other three trip modes, partly because China relies on coal electricity generation, as shown in Figure 5.7. A similar pattern is found in Figure 5.8 waste water.

5.5 Conclusion

In this study, a new approach named Behavioral Life Cycle Assessment (BLCA) that includes explicit, probability-based behavioral inputs influencing choices in the LCA process was developed. BLCA builds on traditional approaches to LCA and follows a similar motivation to that of consequential LCA, but it includes a decision-making process to make it more powerful.

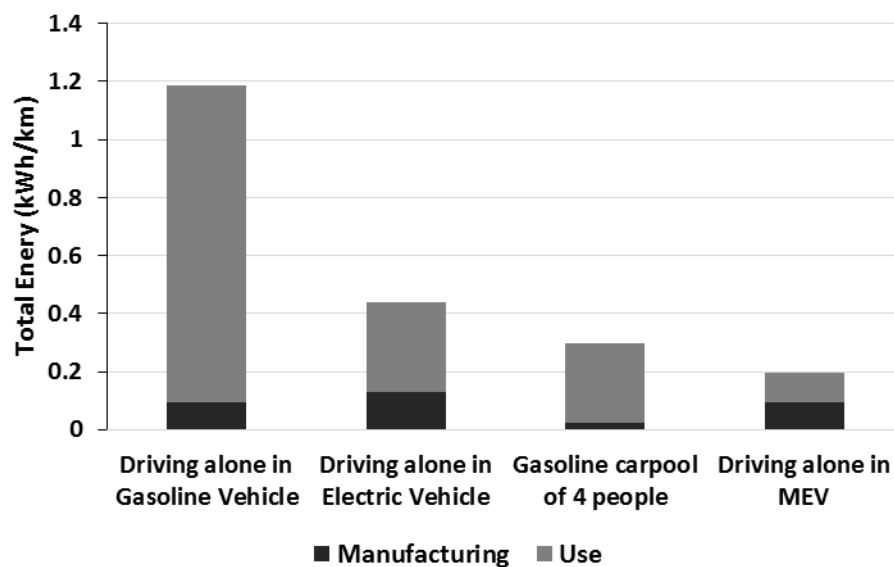


Figure 5.5. Total energy consumption

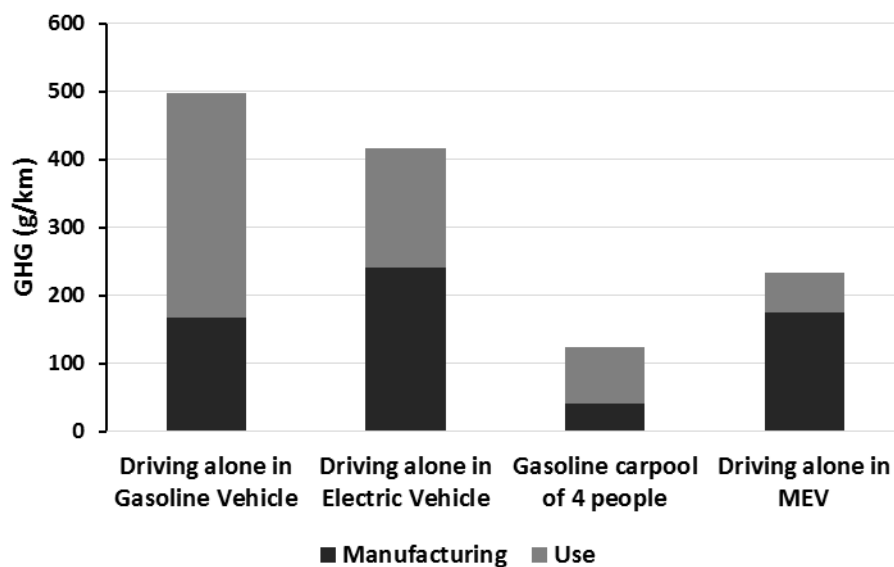


Figure 5.6. Greenhouse gas emission

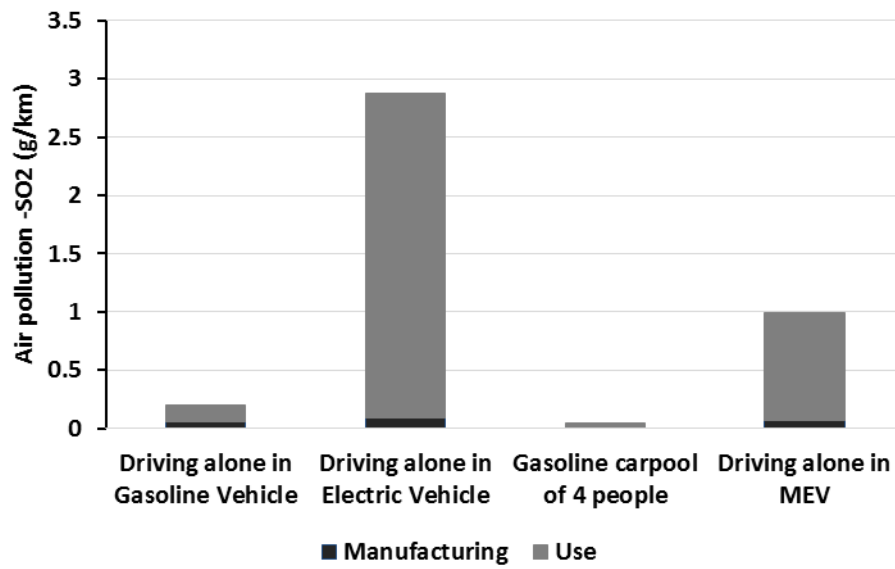


Figure 5.7. Air pollution-SO₂ emission

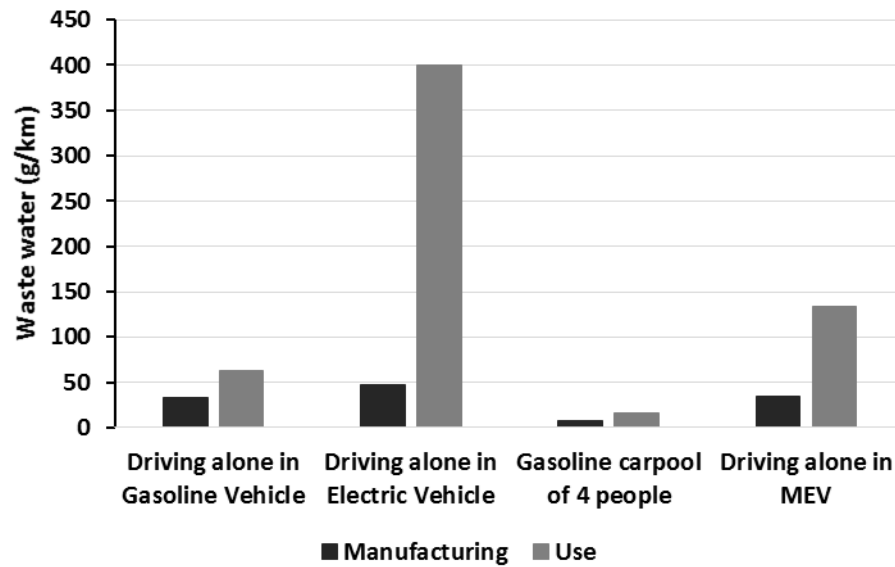


Figure 5.8. Waste water

A case study was conducted using the BLCA framework to compare the environmental impacts of conventional vehicles (CV), plug-in hybrid electric vehicles (PHEV), and battery electric vehicles (BEV) considering choice behavior under different scenarios. The results found that purchase incentives for alternative fuel vehicles influence purchase intentions, ultimately leading to relatively low energy consumption and the lowest CO₂ emission among the nine posited scenarios.

This LCA model is constructed to evaluate the impact of life-cycle assessment of vehicle ownership and usage in China (including manufacturing) on energy consumption, greenhouse gas, and pollution emissions; it uses two major stages, and it is the first China-oriented comprehensive LCA model for transportation system, to the author's knowledge. This China LCA model is flexible to be used independently, or as a part of a BLCA model to evaluate the influence of decision behavior on emissions and energy consumption from a life cycle aspect. A case study using the China LCA model, considering traffic restriction on gasoline vehicles, was evaluated. For daily trips, driving alone in a gasoline vehicle has the highest energy consumption, while MEV has the lowest energy consumption. Though EVs are thought of as a clean transportation mode, this study found that an EV has the highest SO₂ emission compared to the other three trip modes, partly because China relies on coal electricity generation.

There are two major limitations in the study, both of which can be improved in future studies. Firstly, a better defined BLCA model should be developed to fit more behavioral models, including mode choice, trip choice in the transportation area, or other item purchase or choice situations. Secondly, in the China LCA model, the end-of-life part was not included in the full model evaluation because of a lack of data availability. The manufacturing categories are coarse, reflecting the aggregation in the data. Also, electricity generation emission factors in the different areas of China should be considered, especially for evaluating electric vehicle use.

CHAPTER 6

CONCLUSIONS

In this dissertation, four separate but interrelated studies are combined. They discuss the motorization dynamics in the context of socio-demographic, urban form, and environmental constraints, focusing on estimate vehicle purchase choice and perception and use experience towards new transportation modes.

The work in the dissertation includes, first, a study on household vehicle purchase decisions across 59 cities in China with broad geographic, environmental, and socio-economic characteristics. The author focuses on a subset of households who own e-bikes and rely on a telephone survey from an industry customer database. From these responses, the author estimates two three-level hierarchical choice models to assess attributes that contribute to 1) recent car purchases and 2) the intention to buy a car in the near future. The results show that the models are dominated by household characteristics including household income, household size, household vehicle ownership, number of licensed drivers and duration of car ownership. Some geographic, environmental and socio-economic factors have significant influences on car purchase decisions. The author found that household variables dominate the models, with few exogenous variables significantly influencing purchase decisions. Car ownership decreased the chances of purchasing a car. Duration time from first motorized vehicle purchased increase the chances of purchasing a car. Household income and number of licensed drivers increase the chances of purchasing a car. High e-bike ownership increased the chances of purchasing a car which indicates that e-bikes may not be the terminal or substitutes for cars of the motorized pathway. There were a few regional differences as well, with weaker demand in Northeast China. Northwest China and South China have relative stronger car purchase intentions. High taxi density, bus density, population density, and urbanization reduced the likelihood of purchasing a car, meaning advanced public transit could be temper car ownership. Also, advanced public transit usually is built in the bigger cities that may often have more strict regulations or economic barriers to control car ownership. Of the environmental variables, only the number of cold days had significant effect on car purchase decisions. More restrictive e-bike policies did not influence car purchase.

The second study targeted public's future car purchase plans, especially planned vehicle type choice, with the goal of identifying potential customers' attitudes toward and perception of EVs, as well as variables that will influence their car purchase decisions in the future, in order to make policy suggestions from customers' perspective. Compared to CV purchase, being male and having a high household income increased respondents' chances of purchasing EVs (PHEV or BEV). Personal inclination toward CVs decreased the chances of purchasing EVs. Besides these common attributes, plans to get a driver license over the next 3 years decreased respondents' possibility of purchasing PHEVs. The household number of e-bikes increased the chances of purchasing HEVs. The longer respondents had owned a first motorized vehicle, the lower were their chances of purchasing PHEVs. Prior experience with driving or riding in an EV increased the chances of purchasing BEVs. Already having a driver license and a high purchase budget also decreased the chances of purchasing a BEV. A further finding was that the top three preferred EV promotion policies included purchase subsidies, more charging stations, and free battery charging, while another highly confirmed policy recommendation was license plate restriction waiver (chosen by 34% of respondents). Policy recommendations from customers' perspective are therefore offered based on the results, and can be summarized as follows: direct monetary benefits and daily use benefits, effective advertising of promotion policies, focusing on mid-level and below market, with some focus on the top-end market, encouragement of social image influence, development of well-configured micro EVs, and test-driving and free-driving activities to increase experience.

Third, a study presents on the MEVs which is gaining popularity with controversial. This study investigates the motives for MEV choice and purchase, user experience, safety issues and perception of safety, as well as vehicle status. In-depth interviews with MEV owners in Kunming, China reveal that MEV users are predominately retired males with high household income. The average range of their MEVs' is about 100 km, with a maximum speed from 40 to 60 km/h (self-reported). Less than half of them have a driver license. Their purchase motives are most driven by their age or physical limitations, the

convenience and low cost of the vehicle and charging, and the vehicles' low speed. Most users had transitioned from using e-bikes and public transit. Half of the respondents have had crashes before or during the average ownership duration of 3 years. Surprisingly, none of the respondents were concerned about safety issues and were relatively ignorant about traffic safety procedures. Based on these results, the author looks at policy implications and offers recommendations, including standardizing MEVs, imposing a license system for MEVs and their users, enhancing traffic management, and strengthening the insurance system. Despite their shortcomings, MEVs can be an efficient traffic mode for many people to meet their car travel needs using cleaner energy and limiting emissions. Also, MEVs can contribute to vehicle-sharing systems to cover “last mile” trips with small vehicles operating at low cost and with low emissions compared to conventional cars; they can also deal with bad weather, and avoid the sweat, effort, and other problems with bike-sharing systems.

The fourth study developed a new approach named Behavioral Life Cycle Assessment (BLCA) that includes explicit, probability-based behavioral inputs that influence choices in the LCA process is developed. The BLCA model allows policy makers test any combination of possible attributes' influence on the environmental output directly, and helps them make effective and environment-friendly decisions. A case study is conducted using BLCA framework to compare environmental impacts of alternative fuel vehicles choice behavior under different scenarios of policy, technology, charging infrastructure, recharging time, and other attributes. The results found that purchase incentive of alternative fuel vehicles influence purchase intentions, ultimately lead to relatively low energy consumption and the lowest CO₂ emission among nine scenarios. An China LCA model is built for life cycle assessment of energy consumption, greenhouse gas, and pollution emissions based on China's conditions. A case study using China LCA model, considering traffic restriction on gasoline vehicles is evaluated. For daily trips, driving alone in a gasoline vehicle has the highest energy consumption, while MEV has the lowest energy consumption. Driving alone in an EV has the highest SO₂ emission

compared to driving a gasoline car alone, gasoline carpool of 4 people, and driving a micro electric vehicle.

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APPENDIX

**APPENDIX A: E-BIKE OWNER VEHICLE
PURCHASE SURVEY FORM**

1. Where do you live:____(City name)
 - **Place of residence:** Urban____; Suburban____;
Rural____.
2. **Gender:** Male____; Female____.
3. Age:_____.
4. **Occupation:** Student____; Office worker____; factory worker____; Self-employed businessmen ____; Public Institution____; farmer____; Retire____; Others____.
5. **Number of E-bikes in household:**____; Cars____; Motorcycles____.
6. Number of adults in house:____; Number of children(<18 years old) in house:____; Number of licensed drivers:_____.
7. Individual's motorized vehicle purchases (e-bikes, motorcycles and cars) history:
 - 1) E-bikes☐; Motorcycles☐; Cars☐ Price:____;
Bought date:____; Sold date:____; Stolen date:_____.
 - 2) E-bikes☐; Motorcycles☐; Cars☐ Price:____;
Bought date:____; Sold date:____; Stolen date:_____.
 - 3) E-bikes☐; Motorcycles☐; Cars☐ Price:____;
Bought date:____; Sold date:____; Stolen date:_____.
 - 4) E-bikes☐; Motorcycles☐; Cars☐ Price:____;
Bought date:____; Sold date:____; Stolen date:_____.
 - 5) E-bikes☐; Motorcycles☐; Cars☐ Price:____;
Bought date:____; Sold date:____; Stolen date:_____.
8. Your opinion that your vehicle can reflects your status.
(1 means Yes, and 0means No)
 - E-bike:____; Motorcycle:____; Car:_____.
9. Do you intend to buy a car in the next year? Yes☐; No☐.
Fuel type: Gasoline? Yes☐; No☐.
 - Would you consider buying an alt-fuel car (hybrid, plug in electric, LPG, diesel)? Why or why not? **(Multiple choices)**
 - Yes☐; the reason: safe____; convenient____; environment protection____; cost less____; other_____.

- No ☐; the reason: technology is immature__; less choice__; too expensive__; inconvenient for charging__; inconvenient for repair__; didn't know about alt-fuel__; the other__.

10. Have you ever run out of battery power on your e-bike while riding?

- Yes ☐; No ☐.
- Have you ever run out of gasoline on your car while riding?
- Yes ☐; No ☐.

11. On a scale of 1-5 (1 means very difficult and 5 means very easy), How easy is it for you to recharge your e-bike

- At home:__; At work/school:

12. Full day travel diary(yesterday, one way trip):

- From__by__to__; travel distance__travel time__Purpose__;
- From__by__to__; travel distance__travel time__Purpose__;

- From__by__to__; travel distance__travel time__Purpose__;
- From__by__to__; travel distance__travel time__Purpose__;
- From__by__to__; travel distance__travel time__Purpose__;
- From__by__to__; travel distance__travel time__Purpose__;
- From__by__to__; travel distance__travel time__Purpose__;
- From__by__to__; travel distance__travel time__Purpose__;

13. Household income (10,000Yuan):

<2__; 2-4__; 4-6__; 6-8__; 8-10__; 10-12__; 12-14__; >14__.

APPENDIX B: ELECTRIC VEHICLE ACCEPTANCE

SURVEY FORM

1. Age: ☐₁ < 18; ☐₂ 18-30; ☐₃ 30-50; ☐₄ 50-70; ☐₅ > 70
2. Gender: ☐₁ Male; ☐₂ Female
3. Level of completed education:
☐₁ Middle school; ☐₂ High school or technical school; ☐₃ Undergraduate or advanced; ☐₄ Graduate
4. Employment status:
☐₁ Full time; ☐₂ Part time; ☐₃ Unemployed; ☐₄ Retired; ☐₅ Student; ☐₆ Home/other
5. Household No. of adults: __; Household No. of children __; Household No. driver license: __.
6. Household vehicle ownership and primary purpose
 Bicycle: __: ☐₁ Always for commute; ☐₂ Recreation or exercise; ☐₃ Shopping; ☐₄ Other;
 E-bike: __: ☐₁ Always for commute; ☐₂ Recreation or exercise; ☐₃ Shopping; ☐₄ Other;
 Motor: __: ☐₁ Always for commute; ☐₂ Recreation or exercise; ☐₃ Shopping; ☐₄ Other;
 Car: __: ☐₁ Always for commute; ☐₂ Recreation or exercise; ☐₃ Shopping; ☐₄ Other;
7. Currently have a driver's license?
☐₁ Yes, __ years ago; ☐₂ No (I am planning to get one in next __ years);
☐₃ No (I have no plan to get one).
8. For car owners:
Where do you park at home?
☐₁ Public parking space, ☐₁ On street parking, ☐₁ Shared parking space in Xiaogu, ☐₁ Reserved parking space in Xiaogu

Where do you park at work?

☐₁ Public parking space, ☐₁ On street parking, ☐₁ Shared parking space in workplace; ☐₁ Reserved parking space in workplace

9. Within 2 year, do you plan buy a new car?

☐₁ Yes, Gas __, Hybrid __, EV __, Others __; ☐₂ No

10. Household vehicle purchases (e-bikes, motorcycles and cars) history:

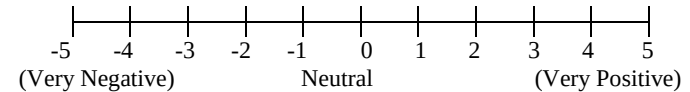
- 6) ☐₁ E-bikes; ☐₂ Motor; ☐₃ Car; Price __; Bought date __; Sold /dispose date __; Stolen/lost date __
- 7) ☐₁ E-bikes; ☐₂ Motor; ☐₃ Car; Price __; Bought date __; Sold /dispose date __; Stolen/lost date __
- 8) ☐₁ E-bikes; ☐₂ Motor; ☐₃ Car; Price __; Bought date __; Sold /dispose date __; Stolen/lost date __
- 9) ☐₁ E-bikes; ☐₂ Motor; ☐₃ Car; Price __; Bought date __; Sold /dispose date __; Stolen/lost date __
- 10) ☐₁ E-bikes; ☐₂ Motor; ☐₃ Car; Price __; Bought date __; Sold /dispose date __; Stolen/lost date __
- 11) ☐₁ E-bikes; ☐₂ Motor; ☐₃ Car; Price __; Bought date __; Sold /dispose date __; Stolen/lost date __

11. Have you ever drive or ride EV? ☐₁ Yes; ☐₂ No

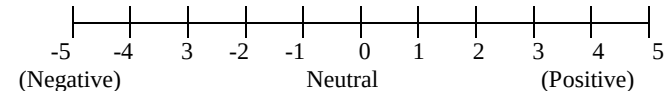
Do you have friends/family or neighbors that own an EV? ☐₁ Yes; ☐₂ No

12. How is your opinion towards to vehicle listed below in general?

E-bike:

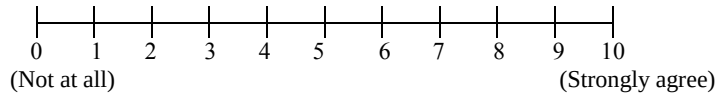


E-vehicle:

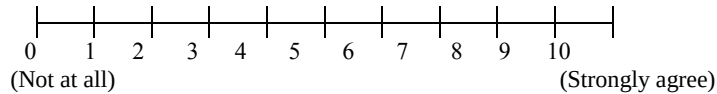


13. Does drive the follow vehicles improve your status or self-image?

E-bike



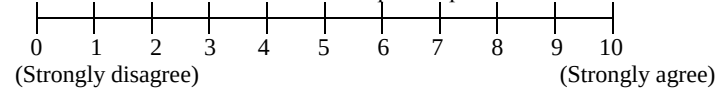
Regular car



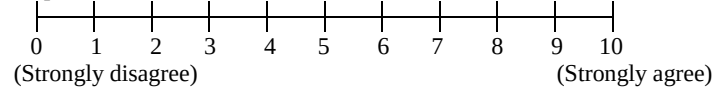
E-vehicle



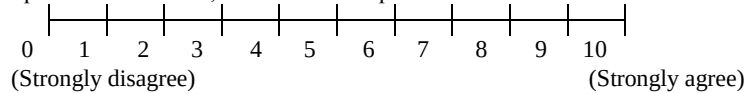
14. I would consider vehicle emissions when I plan to purchase a car.



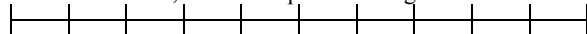
15. I have a positive attitude to EVs because of e-bikes.



16. Compared to normal car, EV is similar in performance.

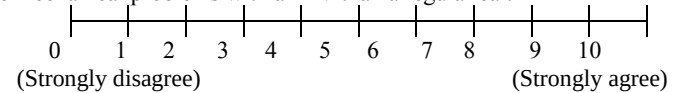


17. Compared to normal car, EV is cheaper over long time term.

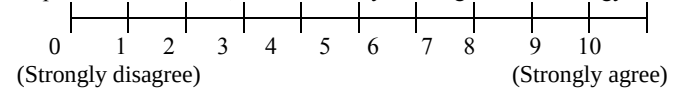


0 1 2 3 4 5 6 7 8 9 10
(Strongly disagree) (Strongly agree)

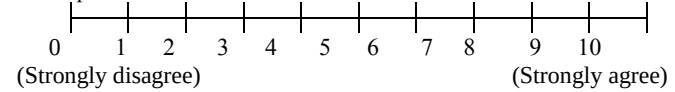
18. To what extent do you agree with the following statement? "I (might) have more mechanical problems with an EV than a regular car."



19. Compared to normal car, EVs are a very exciting new technology.



20. I would prefer to drive a normal car than EV.



21. Please choose three most important benefits related to EVs for you.

- | | |
|--|--|
| Purchase tax exemption | ☐ ₁ |
| Purchase price subsidies | ☐ ₂ |
| License plate restriction waiver | ☐ ₃ |
| License fee exemption | ☐ ₄ |
| Insurance benefits | ☐ ₅ |
| Free battery charging | ☐ ₆ |
| More charging stations | ☐ ₇ |
| Reserved parking spaces | ☐ ₈ |
| Free parking | ☐ ₉ |
| Higher regulation of CO2 emission for regular cars | ☐ ₁₀ |

APPENDIX C: The choice and use of Micro Electric Vehicle

Study goal: I'm here today to talk with you about your use of micro electric vehicle.

Participants' Role: You are the expert in this interview. I want to hear about your thoughts and feelings about the micro electric vehicle you use.

Rules of Participation: I will be audio recording this conversation and taking notes, so that we can be sure to capture and accurately represent what you have to say. All of your answers will be kept confidential and will be reported anonymously. Nobody will be able to link your name to your answers.

Process: I now have a number of questions to ask you. This interview should last from 25 to 35 minutes. This survey is completely voluntary and poses no risk to you in any way. If we come to a question you don't want to answer, just tell me and we'll move on

Topics: We will discuss something related to your experiences with E-bike, including your choice and use of e-bike as well as some of your individual information.

Do you have any questions before we begin?

Part 1 – Purchase Decision

1. What MEV do you have (information on size/shape, wheels, seats, make/model)?
2. What is the range, maximum speed, and battery capacity of you MEV? What type of battery does your MEV have (li-ion or lead)?
3. What was the purchase price and did you also have a purchase tax? Did you finance the purchase with monthly payments?
4. When did you buy the MEV (nearest date please, at least month and year)?
5. What things did you consider while buying the MEV? What was the main factor?
6. What other vehicle options do you have other than the MEV you bought? (other car or motorcycle, other MEVs, e-bikes, bicycle)
7. Did you sell any vehicle before or after buying a MEV?
8. What was your primary mode of transportation before you bought the MEV?
9. Were you influenced by anyone else who had an MEV, and did you influence others to get an MEV?

Part 2 – Usage

1. How many miles have you driven your MEV? (odometer reading)
2. What is your primary trip purpose for riding MEV (e.g., shopping, work)?
3. How often do you bring people with you as a passenger?
4. Think about the last two days, how many trips have you made of all purposes with your MEV? Can you describe those to me?

Trip Time	Purpose	Km Travelled (or Origin and Destination)	Travel time	Alternative mode

5. Do you feel safe when you ride an MEV? If not, why?
6. Have you had any crashes with the MEV? How severe was it?
7. What is the maintenance cost of MEV in a month? How often do you have mechanical or electrical problems? Do you think it is better or worse than gasoline counterpart?
8. What is the thing you like the most about your MEV?

9. What is the thing that you dislike the most about your MEV?
10. Do you primarily use the MEV in the car lane or bike lane?
11. Where do you park the MEV at your home (car park, bike park, sidewalk or other) and do you pay?
12. Where do you park the MEV outside of your home and how much do you pay?
13. Where do you charge you MEV? How often do you charge it?

Part 3 – Future Usage

1. Would you buy this MEV again? If not, what would you go for?
2. In the order of importance, what things would you change in you current MEV?
3. How would you react in the following scenarios:
 - a. Tax subsidy on EV
 - b. Increase in price of gas
 - c. Increase in price of electricity

Part 4 – Demographics

1. Gender
2. What year were you born on?
3. What is your highest level of education?
 - a. Middle school
 - b. High school or technical school
 - c. Undergraduate or advanced
 - d. Graduate
4. How many members are there in your family?
 - a. Number of adults
 - b. Number of children
 - c. Number of driver license
5. Do you have a driver's license?
6. Do you have any physical disabilities or limitations that make travel difficult?
7. How many vehicles does your household own?
Conventional vehicles, motorcycles, e-bike, and bicycles

8. What is the income of your household?

- a. 20,000 RMB or less
- b. 20,000 to 40,000 RMB
- c. 20,000 to 40,000 RMB
- d. 40,000 to 60,000 RMB
- e. 60,000 to 80,000 RMB
- f. 80,000 to 100,000 RMB
- g. 120,000 to 140,000 RMB
- h. 140,000 RMB or more

OPTIONAL: Is there anything else you'd like to tell us regarding MEVs in your city, or thoughts about the survey? Please provide your comments.

Thank you for your time and your participation. Would you like the name and phone number of someone you may call with questions or concerns about this survey?

(IF YES) Please feel free to call: Ziwen Ling, PhD. Student in Transportation Program in the University of Tennessee, zling@vols.utk.edu

VITA

Ziwen Ling was born in Zhenjiang, Jiangsu province in China. She completed her Bachelor's degree in Transportation Engineering at Huazhong University of Science and Technology in Wuhan China. After that, Ms. Ling was recommended for admission to the Tongji University for master degree exempt from admission exam because of outstanding academic performance. She got a master degree in Traffic Information Engineering & Control. After that, Ms. Ling went to the United States, and continued her doctoral study in Transportation Engineering at the University of Tennessee since August 2013. Meanwhile, she also pursued a Master's degree in Business Analytics/Statistics.

During her Ph.D. study, Ms. Ling received several scholarships and awards, including John Harper Scholarship, WTS scholarship by Center Virginia chapter, Bill D. Kervin, Jr. Scholarship, Chancellor Extraordinary Professional Promise Award, TSITE Student Paper Competition Award, and Graduate Student Senate Travel Awards. She served as the vice president of ITE Student Chapter at the University of Tennessee, and was the founded president of Women in Transportation Seminar Student Chapter at the University of Tennessee. Ms. Ling also served as a reviewer for academic journals and conferences. Beyond her research life, Ms. Ling served as the vice president for Chinese Students & Scholars Association at the University of Tennessee for one year. Her research on bicycle crashes at railroad tracks has received ample media coverage worldwide.