From e-bike to car: A study on factors influencing motorization of e-bike users across China

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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. We focus on a subset of households who own e-bikes and rely on a telephone survey from an industry customer database. From these responses, we estimate 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 variable 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. 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 Fig. 1 (Weinert, Ogden et al. 2008, National Bureau of Statistics 2012, Jamerson and Benjamin 2013). In 2009, China became the largest passenger car market in the world, exceeding sales in the USA for the first time (Huo and Wang 2012). 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, Wang et al. 2012). 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.

Fig. 1. Vehicles Sold Since 1998 in China

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 and Benjamin 2013). E-bikes constitute a spectrum of designs from bicycle style e-bikes (BSEB) to scooter style e-bikes (SSEB) (Fig. 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, Ma et al. 2007). 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, Weinert 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, Raghuwanshi et al. 2010) and they experience many conflicts with cars at intersections (Bai, Liu 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).

Fig. 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, Yang 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, we surveyed 947 e-bike owners across 59 Chinese cities. We estimate 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 we focus 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, Ma et al. 2007, Montgomery 2010, Cherry, Yang 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. Background

2.1. 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 and Cervero (2007) 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, Ma et al. 2007). Fig. 3 shows the relative displaced modes derived from those studies.

Fig. 3. Previous e-bike studies and potential mode shift.

2.2. 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, Wang et al. 2007, Ng, Schipper et al. 2010, Wang, Teter et al. 2011, Huo and Wang 2012, Wang, Sun et al. 2012).

A few researchers have attempted to model motorization and purchase decisions at the individual or household level in China (Ni, Kurani 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, Wen et al. 2009, Anastasopoulos, Karlaftis et al. 2012). Some recent work finds that car restriction policies can be very effective at reducing car ownership (Chen and Zhao 2013). Our study investigates household level purchase choices and we draw 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, Wen et al. 2009). Chamon, Mauro et al. (2008) found that higher urbanization levels yielded lower car ownership rates.
- Population density: Lower population density yields lower car ownership rates (Chamon, Mauro et al. 2008, Flamm 2009).
- Road density: high road density encourages car ownership (Chiou, Wen et al. 2009).
- Transit density: Increased transit service reduces car ownership (Chiou, Wen et al. 2009).
- The number of employed family members: More working members of a household results in higher levels of household car ownership (Chiou, Wen et al. 2009, Musti and Kockelman 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: (Chiou, Wen et al.) 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. However, Chen, Takami et al. (2013) 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, Wen et al. 2009, Flamm 2009).
- Income: Higher income is widely identified as the primary factor in increased vehicle ownership (Button, Ngoe et al. 1993, Chu 2002, Zhao and Kockelman 2002, Dargay, Gatley et al. 2007, Ni 2008, Potoglou and Susilo 2008, Flamm 2009, Chen, Takami et al. 2013).
- Gross domestic product per capita: Per capita GDP has a known and strong positive correlation with increasing automobile ownership (Chamon, Mauro 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. Fig. 4 breaks down our data framework into two main variable categories, city level data and individual and household level

data. City level data includes geographic factors that include environmental variables, transportation variables, and socio-economic variables.

Fig. 4. Data framework for car purchase model. Arrows indicate direction of influence on car purchase and ownership from literature.

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 and Susilo 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 and Susilo 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 authors' 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.

3. Methods and Data

3.1. *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. We 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 we rely on an industrial customer dataset, we are 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). Our sample was limited to the most recent five years to assure reliable contact information. On average, we sample 16 respondents from each city (range: 1-37). Fig. 5 shows our 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. Our sample represents some of the most populous areas of China.

The sampling approach randomly identified respondents in our 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.

Fig. 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.

Our response rate was 70%, however, after cleaning data and discarding grossly incomplete surveys, our 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 1, tabulated across China's seven regions (shown in Fig. 5).

Table 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%
	20-40	18.8%	12.8%	13.2%	20.6%	26.6%	18.8%	16.7%	15.3%
Household Income (1,000 Yuan)	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

Data from the interview are supplemented by publicly available statistical data from the city (National Bureau of Statistics 2012). Weather data were gathered from Weather Underground (2013). Data parameters for the cities surveyed, tabulated across different regions, are shown in Table 2. This table reflects the large differences across China's regions.

Table 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.

3.2. Car ownership model

Two models of households' choice of car ownership from 2011 to 2013 and purchase intention for 2014 are proposed (Fig. 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). We 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.

Fig. 6. Framework of the vehicle purchase models

3.3. Hierarchical logit model

We expect 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 Fig. 7. Level 1 is the household level with 947 respondents collected nationwide. Level 2 is the city level with 59 cities we chose from the manufacturer's database and Level 3 includes seven regions. Household-level characteristics correspond to household factors in Fig. 4 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 consists 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 including days with precipitation, 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 is $p_{ijk} = \Pr(y_{ij}=1)$ and p_{ijk} was modeled using a logit link function.

Fig. 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 and Goldman 1995, Goldstein and Jon 1996)).

4. Result and Discussion

4.1. Descriptive Survey Results

The respondent characteristics (Table 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.

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 1000 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 the most 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.

4.2. *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 (Fig. 6). We modeled these discrete outcomes on independent variables that included regional-, city- and household-level variables shown in Fig. 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 3. Some variables are removed because of very low significance levels, such as car purchase price, the number of children, e-bike regulations, etc.

. The results are generally intuitive and expected variables are consistent with other studies on motorization, with a few exceptions. The model is statically 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 3 shows the estimated standard deviation components, indicating small random effects at the regional- and city- levels.

Table 3 Estimates of revealed car purchase model 2011-2013

Indicators			Coefficient	Std.Err.	Z-value	P-value
Fixed-effects Parameters						
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 Parameters						
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	Prob. > Chi-square		0.000	
Wald Chi-square		94.56	Sample Size		911	

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

4.3. *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 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 we do not control for those policies. However the number of e-bikes is an insignificant factor in the revealed model 2011-2013. This 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. 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 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 4 Estimates of intended next-year car purchase model 2013-2014

Indicators			Coefficient	Std. Err.	Z-value	P-value
Fixed-effects Parameters						
	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 Parameters						
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		Prob. > Chi-square		0.000
Wald Chi-square		69.10		Sample size		902

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

4.4. 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 vehicle. 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 (Fig. 8) which is also pointed out by a recent study by Wan, Sperling et al. (2015). While these results are not conclusive, they lend some insight into opportunities or barriers for alternative fuel vehicle adoption.

(a)

(b)

Fig. 8. Reasons for considering an alternative fuel vehicle (a) and reasons for not considering an alternative fuel vehicle (b).

5. 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. This paper adds to the growing body of literature investigating motorization, focusing on household- and city-level factors, rather than national trend analysis. We 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 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., we cannot compare to non-e-bike owners. Nonetheless, we model motorization within a subset of total transportation system users; an important subset on the verge of adopting fully motorized vehicles. Secondly, because this survey was a telephone survey across China, our sample was limited to the dataset spanning 2008-2012 to assure reliable contact information (we 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 authors 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.

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References

- Anastasopoulos, P., M. Karlaftis, J. Haddock and F. Mannering, 2012. Household Automobile and Motorcycle Ownership Analyzed with Random Parameters Bivariate Ordered Probit Model. *Transportation Research Record: Journal of the Transportation Research Board* 2279, 12-20.
- Bai, L., P. Liu, Y. Chen, X. Zhang and W. Wang, 2013. Comparative analysis of the safety effects of electric bikes at signalized intersections. *Transportation Research Part D: Transport and Environment* 20, 48-54.
- Ben-Akiva, M. and S. Lerman, 1974. Some estimation results of a simultaneous model of auto ownership and mode choice to work. *Transportation* 3, 357-376.
- Button, K., N. Ngoe and J. Hine, 1993. Modelling Vehicle Ownership and Use in Low Income Countries. *Journal of Transport Economics and Policy* 27, 51-67.
- Chamon, M., P. Mauro and Y. Okawa, 2008. Mass car ownership in the emerging market giants. *Economic Policy* 23(54): 243-296.
- Chen, B. W., K. Takami, N. Ohmori and N. Harata, 2013. Household Car and Motorcycle Ownership and Transaction Behavior through a Life-Course Approach - a Case of Taipei City. *Proceedings of the Eastern Asia Society for Transportation Studies* 9.
- Chen, X. and J. Zhao, 2013. Bidding to drive: Car license auction policy in Shanghai and its public acceptance. *Transport Policy* 27, 39-52.
- Cherry, C. and R. Cervero, 2007. Use Characteristics and Mode Choice Behavior of Electric Bike Users in China. *Transport Policy* 14, 247-257.
- Cherry, C. R., J. X. Weinert and Y. Xinmiao, 2009. Comparative environmental impacts of electric bikes in China. *Transportation Research Part D: Transport and Environment* 14, 281-290.
- Cherry, C. R., H. Yang, L. Jones and M. He, 2015. Dynamics of Electric Bike Ownership and Use in Kunming China. *Transport Policy* In Review.
- Chiou, Y.-C., C.-H. Wen, S.-H. Tsai and W.-Y. Wang, 2009. Integrated modeling of car/motorcycle ownership, type and usage for estimating energy consumption and emissions. *Transportation Research Part A: Policy and Practice* 43, 665-684.
- Chu, Y.-L., 2002. Automobile Ownership Analysis Using Ordered Probit Models. *Transportation Research Record: Journal of the Transportation Research Board* 1805, 60-67.
- Dargay, J., D. Gately and M. Sommer, 2007. Vehicle Ownership and Income Growth, Worldwide: 1960-2030. *Energy Journal* 28(4).
- De Jong, G. C., 1990. An indirect utility model of car ownership and private car use. *European Economic Review* 34, 971-985.
- Feng, Z., R. P. Raghuwanshi, Z. Xu, D. Huang, C. Zhang and T. Jin, 2010. Electric-bicycle-related injury: a rising traffic injury burden in China. *Injury Prevention* 16, 417-419.
- Flamm, B., 2009. The impacts of environmental knowledge and attitudes on vehicle ownership and use. *Transportation Research Part D: Transport and Environment* 14, 272-279.
- Goldstein, H. and R. Jon, 1996. Improved Approximations for Multilevel Models with Binary Responses. *Journal of the Royal Statistical Society. Series A (Statistics in Society)* 159, 505-513.
- Huo, H. and M. Wang, 2012. Modeling future vehicle sales and stock in China. *Energy Policy* 43, 17-29.

- Huo, H., M. Wang, L. Johnson and D. He, 2007. Projection of Chinese Motor Vehicle Growth, Oil Demand, and CO2 Emissions Through 2050. *Transportation Research Record: Journal of the Transportation Research Board* 2038, 69-77.
- Huo, H., M. Wang, X. Zhang, K. He, H. Gong, K. Jiang, Y. Jin, Y. Shi and X. Yu, 2012. Projection of energy use and greenhouse gas emissions by motor vehicles in China: Policy options and impacts. *Energy Policy* 43, 37-48.
- Jamerson, F. E. and E. Benjamin, 2013. *Electric Bikes Worldwide Reports - Light Electric Vehicles / EV Technology*.
- Montgomery, B. N., 2010. Cycling Trends and Fate in the Face of Bus Rapid Transit: Case Study of Jinan, Shandong Province, China. *Transportation Research Record: Journal of the Transportation Research Board* 2193, 28-36.
- Musti, S. and K. M. Kockelman, 2011. Evolution of the household vehicle fleet: Anticipating fleet composition, PHEV adoption and GHG emissions in Austin, Texas. *Transportation Research Part A: Policy and Practice* 45, 707-720.
- National Bureau of Statistics, 2012. *China Statistical Yearbook*.
- Ng, W.-S., L. Schipper and Y. Chen, 2010. China motorization trends: New directions for crowded cities, 3.
- Ni, M.-C., K. Kurani and D. Sperling, 2010. Motorization in China. *Transportation Research Record: Journal of the Transportation Research Board* 2193, 68-75.
- Ni, M. C., 2008. Motorization, Vehicle Purchase and Use Behavior in China: A Shanghai Survey. PhD Dissertation, University of California, Davis.
- Potoglou, D. and Y. Susilo, 2008. Comparison of Vehicle-Ownership Models. *Transportation Research Record: Journal of the Transportation Research Board* 2076, 97-105.
- Rodriguez, G. and N. Goldman, 1995. An Assessment of Estimation Procedures for Multilevel Models with Binary Responses. *Journal of the Royal Statistical Society. Series A (Statistics in Society)* 158, 73-89.
- Wan, Z., D. Sperling and Y. Wang, 2015. China's electric car frustrations. *Transportation Research Part D: Transport and Environment* 34, 116-121.
- Wang, J., X. Sun, Y. He and S. Hou, 2012. Modeling Motorization Development in China. *Journal of Transportation Technologies* 2, 267-276.
- Wang, Y., J. Teter and D. Sperling, 2011. China's soaring vehicle population: Even greater than forecasted? *Energy Policy* 39, 3296-3306.
- Weather Underground, 2013. *Historic METAR Data*.
- Weinert, J., J. Ogden, D. Sperling and A. Burke, 2008. The future of electric two-wheelers and electric vehicles in China. *Energy Policy* 36, 2544-2555.
- Weinert, J. X., C. T. Ma and C. Cherry, 2007. The Transition to Electric Bikes in China: History and Key Reasons for Rapid Growth. *Transportation* 34, 301-318.
- Weinert, J. X., C. T. Ma, X. M. Yang and C. Cherry, 2007. The Transition to Electric Bikes in China: Effect on Travel Behavior, Mode Shift, and User Safety. Perceptions in a Medium-Sized City. *Transportation Research Record: Journal of the Transportation Research Board* 1938, 62-68.
- Yang, C.-J., 2010. Launching strategy for electric vehicles: Lessons from China and Taiwan. *Technological Forecasting and Social Change* 77, 831-834.
- Zhao, Y. and K. M. Kockelman, 2002. Household vehicle ownership by vehicle type: application of a multivariate negative binomial model. 81st Annual Meeting of the Transportation Research Board. Washington, DC.