Consumer Preferences for Hybrid and Electric Vehicles in China and the United States – Implications for Policy and Environment

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Abstract: We model consumer preferences for hybrid and electric vehicle technologies in both China and the U.S. using data from choice-based conjoint surveys fielded in both countries. We find U.S. consumer willingness-to-pay (WTP) for battery electric vehicle (BEV) technology is \$13,000–\$17,000 lower than a conventional gasoline vehicle with identical attributes. This is larger than what can be gained in fuel cost savings even if vehicle purchase prices were comparable. In contrast, Chinese consumer WTP for BEV technology is within \$2,000 of comparable conventional vehicles and in some cases (with sufficient range) could be higher. Based on measured preferences, while current U.S. subsidies are sufficient to drive mainstream adoption of plug-in hybrid electric vehicles (PHEVs) and insufficient for BEVs, current Chinese subsidies imply the opposite, indicating a greater potential for early BEV adoption in China. Given the higher emissions associated with electricity generation in China, a transition to BEVs may reduce oil consumption at the expense of increased air pollution and greenhouse gas emissions, and a technology transition in China could influence global technology trajectories.

1. INTRODUCTION

1.1 Vehicle Electrification

China and the United States are the two largest car markets in the world today. In 2009, China became (and has since remained) the world's largest passenger vehicle market, selling 13.6 million units compared to the U.S.'s lowest annual sales in 27 years of 10.6 million units (Liu, 2009), (CATARC, 2009). Both nations have large amounts of emissions and oil consumption associated with passenger car use. From 2000 to 2009, China's annual oil consumption nearly doubled, and passenger cars accounted for about 20% of the total oil demand growth during that period (Ma, Fu, Li, & Liu, 2012). Together with the U.S., the two nations contribute to approximately one third of oil consumed globally every year (U.S. EIA, 2012). In the U.S., passenger cars are responsible for 20% of annual green house gas (GHG) emissions as well as 40% of volatile organic compound (VOC) emissions, 77% of carbon monoxide (CO) emissions, and 49% of nitrogen dioxide (NOx) emissions (U.S. EIA, 2011). In China the emissions levels are comparable, with even higher portions of CO and NOx emissions attributable to passenger vehicles (Gallagher, 2006).

Transitioning the passenger vehicle fuel source from gasoline to electricity, "vehicle electrification," is one of the more promising options for near-term reduction of both oil consumption and harmful emissions from passenger cars. Studies have shown that, depending on the grid mix and vehicle design, PHEVs could reduce total GHG emissions by as much as 35% and transfer vehicle emissions from urban centers to power plants, thereby reducing air pollution damages (Michalek et al., 2011), (Samaras & Meisterling, 2008), (Bradley & Frank, 2009), (Hawkins et al., 2012), (Ji et al., 2011), (Peterson et al., 2011). The three main technologies available for vehicle electrification are hybrid vehicles (HEVs), plug-in hybrid vehicles (PHEVs), and battery electric vehicles (BEVs). HEVs consume gasoline and utilize a small electric motor and small battery pack to improve fuel efficiency, mostly through regenerative breaking, engine downsizing, engine shutoff at idle, and power management. PHEVs are similar to HEVs except typically have a larger battery pack and can be driven for short distances (usually less than 40 miles) using only electricity before switching to gasoline for an extended range. PHEVs can also be plugged-in to electrical outlets for stationary charging. BEVs run purely on electricity and do not use gasoline. They have large battery packs and large electric motors and must be plugged in to an electrical outlet to charge.

1.2 Government Incentives and Consumer Preferences

To incentivize the adoption of these technologies, both the U.S. and China offer subsidies for PHEVs and BEVs that increase proportionally with the battery capacity from a baseline up to a maximum value (ARRA, 2009) (Scott, 2010). Nevertheless, mainstream adoption of hybrid and electric vehicles will not occur if consumers do not want them. Consumer preferences play an important role in technology adoption, and understanding those preferences allows us to begin to answer related policy questions, such as what would need to happen (e.g. changing key vehicle attributes, costs, or policy options) to achieve mainstream adoption of hybrid and electric vehicles, and identify tensions between consumer preferences, government incentives, and social benefits.

Because of the size of China's passenger vehicle market, the future of global vehicle technologies is tied to market trends in China. In 2011, one in four passenger vehicles made globally were made in China, and at the same time China is becoming a central market for many global automakers. Volkswagen, for example, now sells one quarter of its global sales in China (LMC Automotive, 2011). As the world's leading automakers continue to consider preferences of Chinese consumers during strategic planning of vehicle platforms, the trends in China's vehicle market have the potential to change the competitiveness of emerging technologies worldwide.

1.3 Research Questions

We design and field a controlled conjoint experiment in both China and the U.S. to measure preferences and build discrete choice models to quantify those preferences for different vehicle technologies and attributes. We focus our analysis on three primary research questions:

1. How do U.S. and Chinese preferences for vehicle attributes compare?
2. How would current plug-in vehicles compete against their conventional counterparts in the U.S. and China?
3. Under what conditions would the average car buyer be indifferent between a conventional gasoline car and its plug-in counterpart?

We address question 1 by estimating consumer willingness-to-pay for incremental changes in vehicle attributes based on the conjoint data. We address question 2 via market simulations where pairs of selected plug-in vehicles and their conventional counterparts compete against one another in the U.S. and Chinese markets. Finally, we address question 3 by calculating the amount of change in purchase price and gasoline price needed to make the average consumer indifferent between plug-in vehicles and their gasoline counterparts.

2. Method

To measure consumer preferences, we apply choice-based conjoint analysis to design and field equivalent controlled survey experiments in China and the U.S. during the summer of 2012 and spring of 2013. We use the resulting individual-level choice data to estimate several random utility discrete choice models (Train, 2009).

In choice-based conjoint analysis, participants in a survey experiment are asked to compare several product profiles (each defined by a set of attributes, such as price, brand, type, etc.) and choose the product they are most likely to buy. Discrete choice models are then used to infer the relative importance of each attribute in determining consumer choice. Because the experiment is controlled, we avoid many of the pitfalls of using historic sales data, such as multicolinearity, endogeneity, missing attributes, model misspecification, and a lack of information about consumers, the attributes they observed, and the alternatives they considered (Feit et al., 2010), (Louviere et al., 2000). However, the key disadvantage of controlled conjoint experiments is the potential difference between a consumer's choice behavior in the hypothetical survey conditions we create versus choice behavior in the market when real money is being spent in the point-of-purchase context. Given the limited history of plug-in vehicle sales in both markets and the complications of regional regulations, supply limitations, incentives, and non-representative early-adopter preferences, stated choice methods offer the best potential for understanding potential future mainstream adoption, and we attempt to minimize potential bias as much as possible in survey design.

2.1 Survey Design

In designing the choice experiment we sought to balance the cognitive load and respondent burden against choosing a design that would be informative and match as closely as possible the survey-taker's experience to the experience of making product choices in the marketplace. The design chosen was randomized. Based on results from several preparatory interviews and pilot surveys, we designed a field experiment with three main parts: 1) a vehicle image section, 2) a choice experiment section, and 3) questions on demographics, experience, knowledge, and attitudes towards driving and electrified vehicles. In addition, we also recorded information about each respondent's previous vehicle purchases as well as daily and annual vehicle miles traveled (VMT). We describe each part in turn.

Part 1: Vehicle Image Selection

Given the limited number of HEVs, PHEVs, and BEVs currently available in the market, some respondents might assume an associated vehicle aesthetic when considering a powertrain type (e.g. visualizing a Toyota Prius when shown an alternative with an HEV powertrain). To control for potential bias from inferred vehicle aesthetics, we ask respondents early in the survey to choose an image of a vehicle they found visually appealing. Once selected, we hold this image fixed at the top of each choice question, informing respondents that each vehicle is exactly the same except for differences in the attributes shown in the choice question (similar to selecting a vehicle options package).

Part 2: Choice Experiment

The choice section of the conjoint survey consists of 15 randomized choice tasks and one fixed choice task. Each choice task includes three options – a compromise between cognitive load and necessary sample size informed by feedback and responses from pilot surveys conducted during the spring of 2012. The fixed choice task was always shown first as an example choice question with a clearly dominant alternative (i.e. all attributes identical across alternatives except one was cheaper and more efficient), which was used as a screener question to identify respondents who did not understand the task or did not take it seriously. Figure 1 below is an example of a choice task for the U.S. survey.

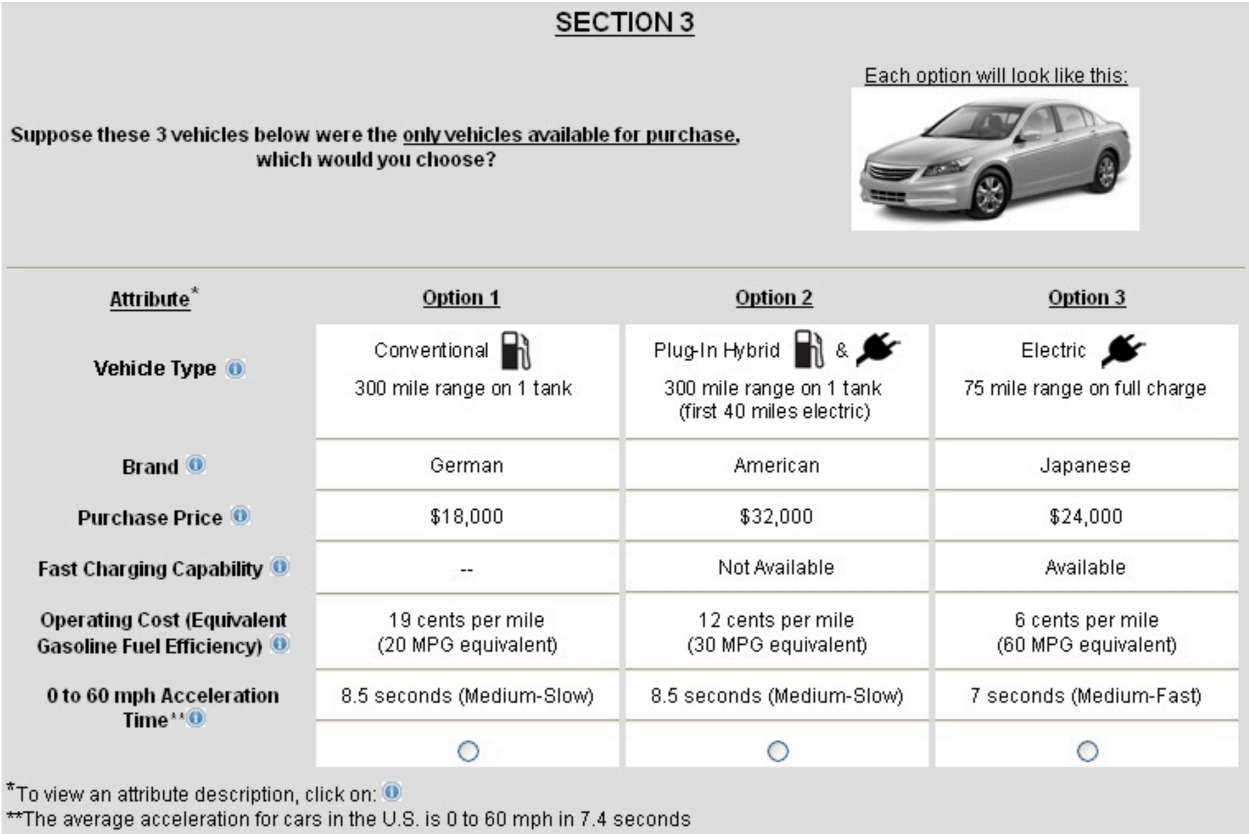

FIGURE 1 Example choice task for the U.S. The attribute values (levels) in each choice task were randomly assigned for each question and each respondent.

Each alternative has six attributes (type, brand, purchase price, fast charging capability, fuel cost, and acceleration), each with several levels. The experiment design was fully randomized, meaning that the combination of attribute levels shown for any given alternative was randomly assigned and generated using Sawtooth Software (Chrzan & Orme, 2002). For vehicle type, we included conventional vehicles (CVs) and HEVs as well as PHEVs and BEVs with varying all-electric range (AER). The AERs for the China survey were given in the km equivalent of the U.S. ranges within 5% difference. Brand was represented using country of origin (e.g.: "Volkswagen" would be "German," and "Ford" would be "American") to maintain a statistically manageable number of alternatives. The "Fast Charging Capability" attribute was a binary attribute indicating whether or not a plug-in vehicle had the ability to charge in under 15 minutes (the attribute was hidden for CV and HEV powertrains). Operating cost was presented as cost per mile driven due to the mixed fuel types of the different vehicles. The cost-equivalent fuel economy for a conventional gasoline vehicle was provided in parenthesis for reference, since it is a more familiar metric for respondents. The cost-equivalent fuel economy was computed using average gasoline prices in each country ($3.60/gal in the U.S. and $4.40/gal in China) and was presented in the most commonly used form for each country (miles/gallon in the U.S. and L/100km in China). Finally, acceleration performance was provided as the time to accelerate from 0 to 60 miles per hour in the U.S. (0 to 100 kilometers per hour in China).

Vehicle type, brand, and fast charging capability were the same in each country as well as for cars and SUVs. For purchase price, operating cost, and acceleration time, the levels were different between each country as well as between cars and SUVs. We chose the levels for these attributes based on the respective sales distributions of vehicles in the 2011 market (approximately the 5th, 25th, 50th, 75th, and 95th percentile values in each case) to represent the range of attributes relevant for each market. Table 1 below summarizes the attributes and levels used in each country for the experiment.

TABLE 1

Attributes and levels used in U.S. & China choice experiments

Attributes	Levels	
U.S. & China	Cars & SUVs	
1. Vehicle Type (range in miles)	CV / HEV / BEV75 / BEV100 / BEV150 / PHEV10 / PHEV 20 /PHEV40 /	
2. Brand	German / American / Japanese / Chinese / S. Korean	
3. Fast Charging Capability	Available / Not Available (applicable for PEVs only)	
U.S.	Cars	SUVs
4. Purchase Price ($1,000 USD)	15 / 18 / 24 / 32 / 50	20 / 25 / 30 / 37 / 50
5. Operating Cost (U.S. cents /mile)	6 / 9 / 12/ 19	9 / 13 / 19 / 23
6. 0 to 60 mph Acceleration Time (s)	5.5 / 7 / 8.5 / 10	7 / 8 / 9 / 10
China	Cars	SUVs
4. Purchase Price (¥1,000 RMB)	60 / 90 / 130 / 170 / 250	75 / 130 / 200 / 330 / 500
5. Operating Cost (RMB cents /km)	34 / 42 / 49 / 61	46 / 57 / 68 / 80
6. 0 to 100 km/hr Acceleration Time (s)	9 / 11 / 13 / 15	9 / 11 / 13 / 15

Part 3: Questions on Demographics, Experience, Knowledge, and Attitudes

The last section of the survey contained demographic questions as well as questions related to personal experience, attitudes, and knowledge about driving and electrified vehicles. We use a 5-point likert scale to rate preferences for attributes not included in the choice section including storage space, reliability, safety, towing capacity, and outward appearance. We used the same scale to ask about environmental attitudes. We also asked about access to parking, access to vehicle charging, income, sex, age, household size, zip code, education level, number of children, and marital status.

2.2 Data Collection

In both countries respondents filled out computer-based surveys that were equivalent in content and in presentation except for translation and the values of some attribute levels, which were each calibrated to the values in the corresponding existing vehicle market. The Chinese translation was performed by one translator and was back-translated into English by another translator to assess the translation and ensure equivalent language and descriptions in both surveys. In China most vehicle purchases are made in large cities, so we conducted surveys in-person in July and August 2012 using laptop computers in four major cities (Beijing, Shanghai, Shenzhen, and Chengdu) chosen for their large passenger vehicle markets as well as geographic diversity. In the U.S. vehicle sales are more distributed, so the survey was fielded both online using Amazon Mechanical Turk (AMT) in September 2012, and in person at the Pittsburgh Auto Show in February 2013 to diversify the sample.

In China we collected 860 respondents and discarded 120 (14%) based on screening criteria for a total of 740 qualified respondents. We also discarded all data collected in Beijing since it appears to include many random responses, which we feel is possible for a number of reasons. First, the Beijing data was fielded outside in the sun on hot summer days making it uncomfortable and difficult to take the survey. Second, Beijing was the only city for which the primary author was unable to be present to ensure the survey was correctly set up and administered. When including the Beijing data, we find that all effects in China remain comparable, but just larger in magnitude. Our final China sample was 560 (448 cars and 112 SUVs).

In the U.S. we collected 398 respondents online and 154 at the Pittsburgh Auto show for a total of 552. We discarded 42 (5.8%) based on screening criteria for a total sample size of 510 (384 cars and 126 SUVs). Screening criteria for discarding responses included: 1) completing the survey in under 6 minutes, the approximate minimum time for completing the survey without randomly answering the choice questions, or 2) failing to choose the dominant choice in the example question which was fixed for each respondent, indicating that the respondent either misunderstood the task or did not pay close attention to the choice question. The sample of respondents was constrained to individuals who recently purchased a vehicle within the last year or those who have intentions of purchasing a car within the next two years. For the analysis in this paper, we only examine preferences for the car respondents, not SUVs.

We compared our sample to that of a much larger, representative new car buyer survey conducted by Maritz in both the U.S. and China and found we oversampled younger, less wealthy individuals in each country, with particularly strong oversampling in the U.S. To account for these differences, we weighted the respondents using least squares optimization to match the age and income cumulative distribution functions from our survey to those from the Maritz survey as closely as possible subject to lower and upper constraints on the weights to avoid placing too much weight on any one respondent. About two-thirds of the respondents in China were first-time vehicle buyers, versus only about 6% in the U.S.

TABLE 2

Summary of sample demographic information in our survey, our weighted results, and the reference Maritz survey (means shown with standard deviation in parentheses)

	U.S.			China		
	Our Survey	Weighted	Maritz Survey	Our Survey	Weighted	Maritz Survey
Household Income ($1k)	58.0 (28.6)	74.5	74.8 (27.4)	23.9 (14.4)	26	26.1 (18.2)
Age	33.9 (12.7)	51	53.1 (12.6)	33.3 (10.4)	34.8	34.8 (7.9)
Number of Children	0.6 (1.1)	1.4	0.4 (0.5)	0.6 (0.6)	0.7	0.7 (0.6)
Household Size	2.7 (1.3)	2.7	2.5 (1.2)	2.7 (1)	3.3	3.2 (1.0)
Percent With No Children	68.50%	68.50%	75.00%	46.40%	46.40%	36.40%
Percent Female	36.50%	36.50%	39.30%	40.20%	40.20%	27.30%
Percent Married	46.90%	46.90%	73.50%	57.80%	57.80%	85.60%
n	384	384	161,903	448	448	13,469

2.3 Model Specification

Using a random utility model, we assume each consumer i on each choice occasion (each conjoint question) t will select among a set of alternatives $j \in J_{it}$ the one that offers the greatest utility u_{ijt}:

$$u_{ijt} = v_{ij} + \varepsilon_{ijt}, \quad j \in J_{it}, \tag{1}$$

Here, utility is decomposed into an observable component v_{ij} and an unobservable component ε_{ijt}. The observable component v_{ij} is a function of the observable attributes of the product $\mathbf{x}_j$, so that $v_{ij} = f_i(\mathbf{x}_j)$. This function is often presumed to be linear, so that $v_{ij} = \boldsymbol{\beta}_i' \mathbf{x}_j$, where $\boldsymbol{\beta}_i$ is a vector of coefficients that define the relative importance of the product attributes $\mathbf{x}_j$ in driving choice. The unobservable component ε_{ijt}, which captures the factors not included in v_{ij}, is treated as a random variable. Utility u_{ijt} is therefore a random variable, and the probability that consumer i will select product j on choice occasion t is the probability that $u_{ijt} > u_{ikt}$ $\forall k \in J_{it} \setminus j$. We employ variants of the logit model (one of the most widely adopted choice models), which assume that the unobservable utility ε_{ijt} has an independent and identically distributed extreme value distribution, yielding a closed-form expression for choice probabilities given by

$$P_{ijt} = \frac{e^{v_{ij}}}{\sum_{k \in J_{it}} e^{v_{ik}}}. \tag{2}$$

In order to relax some limiting assumptions from the logit model (e.g. the independence from irrelevant alternatives (IIA) property (Train, 2009)), we also apply a mixed logit model (McFadden & Train, 2000), which treats model coefficients $\boldsymbol{\beta}_i$ as random variables whose parameters are to be estimated, allowing for systematic heterogeneity of preferences across the population and more general substitution patterns. While the logit model effectively assumes $\boldsymbol{\beta}_i = \boldsymbol{\beta}\ \forall i$ and captures variation in preferences across individuals only in the error term ε_{ijt}, the mixed logit model instead assumes that the $\boldsymbol{\beta}_i$ coefficients are drawn from a distribution. For tractability, we assume each element β_{in} of the vector $\boldsymbol{\beta}_i$ is drawn from an independent distribution, where $\beta_{in} \sim N(\mu_n, \sigma_n^2)$ for attributes expected to have non-monotonic preferences (e.g.: brand) and $\beta_{in} \sim \ln N(\mu_n, \sigma_n^2)$ for attributes expected to have monotonic preferences (e.g.: price and operating cost). Here we use "monotonic" to mean the same sign for all individuals. We test multiple models with different heterogeneity specifications.

Equation (3) below shows the explicit model used for this study, with explanations of variable names shown in Table 3. Finally, in order to separate the difference in utility for the U.S. sample from that of the Chinese sample, we interact a dummy variable, δ^{USA}, for whether the respondent was from the U.S. sample with each covariate in Equation (3). This gives us coefficients for the Chinese sample and the *difference between* the U.S. and Chinese samples.

$$\begin{aligned}
\text{Type:}\quad & U_j = \beta_1 x_j^{\text{HEV}} + \beta_2 x_j^{\text{PHEV}} + \beta_3 x_j^{\text{BEV}} + \beta_4 x_j^{\text{PHEV}} x_j^{\text{PHEV_AER}} + \beta_5 x_j^{\text{BEV}} x_j^{\text{BEV_AER}} \\
\text{Cost \& Performance:}\quad & + \beta_6 x_j^{\text{PRICE}} + \beta_7 x_j^{\text{PHEV}} x_j^{\text{FASTCHARGE}} + \beta_8 x_j^{\text{BEV}} x_j^{\text{FASTCHARGE}} + \beta_9 x_j^{\text{OPCOST}} + \beta_{10} x_j^{\text{ACCEL}} \\
\text{Brand:}\quad & + \beta_{11} x_j^{\text{AMERICAN}} + \beta_{12} x_j^{\text{JAPANESE}} + \beta_{13} x_j^{\text{CHINESE}} + \beta_{14} x_j^{\text{SKOREAN}} \\
\text{Error:}\quad & + \varepsilon_{nj}
\end{aligned} \tag{3}$$

TABLE 3
Description of model variables

Variable	Description
x_j^{HEV}	Dummy for HEV vehicle type {1: yes, 0: no} (base level is CV)
x_j^{PHEV}	Dummy for PHEV vehicle type; baseline is PHEV10 {1: yes, 0: no}
x_j^{BEV}	Dummy for BEV vehicle type; baseline is BEV75 {1: yes, 0: no}
$x_j^{\text{PHEV\_AER}}$	All electric range (AER) for PHEV types beyond 10 miles {0 for PHEV10}
$x_j^{\text{BEV\_AER}}$	All electric range (AER) for BEV types beyond 75 miles {0 for BEV75}
x_j^{PRICE}	Price paid in thousands of US dollars
$x_j^{\text{FASTCHARGE}}$	Dummy for whether or not the vehicle can be rapidly charged in less than 15 minutes {1: yes, 0: no}*
x_j^{OPCOST}	Operating cost in US cents per mile
x_j^{ACCEL}	Time required to accelerate from 0 to 60 mph (seconds)
x_j^{AMERICAN}	Dummy for brand of American origin {1: yes, 0: no} (base level is German)
x_j^{JAPANESE}	Dummy for brand of Japanese origin {1: yes, 0: no}
x_j^{CHINESE}	Dummy for brand of Chinese origin {1: yes, 0: no}
x_j^{SKOREAN}	Dummy for brand of S. Korean origin {1: yes, 0: no}

* $x_j^{\text{FASTCHARGE}}$ is interacted with x_j^{PHEV} and x_j^{BEV} since the attribute was hidden for CV and HEV powertrains.

3. Results

We examine three primary models. In each model, the dataset consists of all respondents from both countries excluding the Beijing sample and the invalid responses. We estimate the main effects of each vehicle attribute as well as their interactions with a dummy variable for the U.S. to identify statistically significant differences between the two countries. In model 1a, we fit a logit model with fixed coefficients for all covariates in Equation (3). In model 1b, we fit the same model but weight the sample by income and age (all other models include the same weighting). In model 2, we fit a mixed logit model where each coefficient is modeled as independently normally distributed, so we estimate the mean and variance of the distribution for each coefficient. Finally, model 3 is the same as model 2 except the coefficients for x_j^{PRICE} and x_j^{OPCOST} are modeled as log-normally distributed rather than normally distributed, enforcing monotonicity of preferences for these attributes. The estimates from each of these models are presented in Table 4. Note that we present the coefficients as *mu* and *sigma*, referring to the parameters of the assumed distribution on $\boldsymbol{\beta}_i$ (e.g. $\beta_{in} \sim N(\mu_n, \sigma_n^2)$ or $\beta_{in} \sim \ln N(\mu_n, \sigma_n^2)$).

TABLE 4

Regression Coefficients for Models 1a, 1b, 2, and 3

	Attribute	Coef.	Model 1a	Model 1b	Model 2	Model 3
Powertrain Type (base = CV)	HEV	mu	0.208 (0.0636)**	0.168 (0.0599)**	0.243 (0.0739)**	0.289 (0.0737)***
		sigma	--	--	0.144 (0.0991)	-0.245 (0.0931)**
	PHEV	mu	-0.04 (0.0636)	-0.051 (0.0602)	0.022 (0.0737)	0.007 (0.0733)
		sigma	--	--	0.179 (0.0736)*	0.274 (0.0583)***
	BEV	mu	-0.29 (0.0654)***	-0.254 (0.0615)***	-0.391 (0.0818)***	-0.152 (0.0831)
		sigma	--	--	-0.768 (0.0559)***	0.87 (0.0514)***
	PHEV*PHEV_AER	mu	0.003 (0.0019)	0.003 (0.0018).	0.005 (0.0023)*	0.003 (0.0022)
		sigma	--	--	-0.004 (0.0026)	0 (0.0027)
	BEV*BEV_AER	mu	0.003 (0.0008)**	0.004 (0.0008)***	0.003 (0.001)**	0.004 (0.001)***
		sigma	--	--	0.01 (0.0011)***	0.006 (0.0018)***
Brand (base = German)	American	mu	-0.271 (0.0496)***	-0.355 (0.0463)***	-0.466 (0.0638)***	-0.487 (0.0652)***
		sigma	--	--	0.75 (0.0654)***	0.726 (0.0663)***
	Japanese	mu	-0.468 (0.05)***	-0.585 (0.0469)***	-0.751 (0.0607)***	-0.769 (0.0632)***
		sigma	--	--	0.461 (0.0824)***	0.624 (0.0612)***
	Chinese	mu	-0.231 (0.0487)***	-0.316 (0.0455)***	-0.484 (0.0669)***	-0.411 (0.0623)***
		sigma	--	--	-0.846 (0.0634)***	0.612 (0.0851)***
	SKorean	mu	-0.467 (0.0498)***	-0.622 (0.0472)***	-0.788 (0.0601)***	-0.79 (0.0588)***
		sigma	--	--	-0.394 (0.0631)***	-0.306 (0.0867)***
Cost and Performance	Price	mu	-0.035 (0.0016)***	-0.034 (0.0015)***	-0.049 (0.0034)***	-3.31 (0.0765)***
		sigma	--	--	0.079 (0.0032)***	1.365 (0.0611)***
	OpCost	mu	-0.103 (0.0066)***	-0.111 (0.0061)***	-0.16 (0.0093)***	-2.183 (0.0934)***
		sigma	--	--	0.13 (0.007)***	0.975 (0.0693)***
	Acceleration	mu	-0.172 (0.0074)***	-0.154 (0.0069)***	-0.229 (0.013)***	-0.207 (0.0131)***
		sigma	--	--	0.243 (0.0131)***	0.231 (0.0117)***
	PHEV*FastCharge	mu	0.263 (0.0507)***	0.24 (0.0478)***	0.267 (0.0589)***	0.306 (0.0574)***
		sigma	--	--	-0.271 (0.085)**	0.037 (0.0964)
	BEV*FastCharge	mu	0.198 (0.0524)***	0.241 (0.049)***	0.28 (0.064)***	0.261 (0.0639)***
		sigma	--	--	0.423 (0.1257)***	-0.46 (0.0857)***
Variation by Country	USA*HEV	mu	-0.148 (0.0974)	-0.228 (0.097)*	-0.224 (0.1208).	-0.349 (0.122)**
	USA*PHEV	mu	0.128 (0.0976)	0.071 (0.0992)	-0.042 (0.1232)	-0.083 (0.1231)
	USA*BEV	mu	-0.866 (0.1043)***	-0.831 (0.1045)***	-1.145 (0.1403)***	-1.471 (0.1447)***
	USA*PHEV*PHEV_AER	mu	0 (0.0031)	0.001 (0.0031)	0.005 (0.0039)	0.005 (0.0039)
	USA*BEV*BEV_AER	mu	0.004 (0.0014)**	0.001 (0.0014)	0.005 (0.0019)**	0.003 (0.0018)
	USA*American	mu	0.446 (0.0769)***	0.783 (0.076)***	1.057 (0.1057)***	1.124 (0.1055)***
	USA*Japanese	mu	0.442 (0.0769)***	0.633 (0.077)***	0.801 (0.1013)***	0.996 (0.1071)***
	USA*Chinese	mu	-0.526 (0.0791)***	-0.678 (0.0807)***	-0.91 (0.116)***	-0.925 (0.1132)***
	USA*SKorean	mu	0.022 (0.0787)	0.124 (0.0797)	0.18 (0.1014).	0.218 (0.1009)*
	USA*Price	mu	-0.039 (0.0026)***	-0.019 (0.0024)***	-0.04 (0.0055)***	-0.002 (0.0039)
	USA*OpCost	mu	-0.018 (0.0079)*	0.028 (0.0075)***	0.039 (0.0126)**	0.017 (0.0108)
	USA*Acceleration	mu	0.047 (0.0138)***	0.093 (0.0138)***	0.112 (0.0231)***	0.09 (0.0241)***
	USA*PHEV*FastCharge	mu	-0.051 (0.0785)	-0.034 (0.0788)	0.084 (0.0999)	0.006 (0.0971)
	USA*BEV*FastCharge	mu	0.018 (0.085)	-0.068 (0.0854)	0.019 (0.1114)	0.028 (0.1133)
Fit	Log-likihood:		-11276	-11786	-10830	-10808
	Likelihood Ratio Index (in-sample):		0.1776	0.1404	0.2101	0.2117
	Likelihood Ratio Index (hold-out):		0.1939	0.1939	0.1813	0.1864
	AIC:		22608	23628	21744	21700

Signif. codes: '***' <=0.001, '**' <= 0.01, '*'<= 0.05. Standard errors of estimates are presented in parenthesis.

Comparing model fit across the models, the log-likelihood increases when moving from a fixed coefficient logit model (model 1) to a mixed logit model with random coefficients (models 2 and 3), meaning a better fit to the data (as is expected since the mixed logit models have more parameters). The Akaike information criterion (AIC) also decreases, suggesting the mixed logit models do not over-fit the data compared to the simple logit model. Another metric for comparing model fit is the likelihood ratio index (LRI), which is simply a monotonic transformation of the log-likelihood, but is perhaps more easily interpreted since it ranges from zero (when the estimated parameters are no better than zero parameters) to one, when the estimated parameters perfectly predict the choices (Train, 2009). The in-sample LRI is calculated by using the entire dataset to estimate a model that is used to predict the choices made by the decisions makers. The hold-out LRI is calculated by estimating the model on approximately 90% of the data, and then using the resulting model to predict the remaining randomly held out data. While the in-sample LRI improves when moving from logit to mixed logit, the hold-out LRI decreases, which suggests some degree of over-fitting.

We use model 3 as a base model because in addition to having the best log-likelihood, best in-sample LRI, and best AIC, it also enforces monotonic preferences for price and operating cost, which is much more consistent with reality. For example, while model 2 is similar in fit to model 3, it also suggests that approximately 27% of the Chinese sample would have a positive price coefficient, meaning that almost one third of the respondents would *prefer* to pay more for the same vehicle than less. For the rest of the analysis we present results from model 3; however, over all three models the following observations can be made:

1. Both U.S. and Chinese consumers dislike the BEV powertrain relative to alternatives, and both prefer lower price, operating cost, and acceleration time as well as fast-charging capabilities for both PHEVs and BEVs.
2. Compared to Chinese consumers, U.S. consumers perceive substantially more disutility for BEV powertrains and are less sensitive to acceleration.
3. Brand is an important factor for both American and Chinese consumers. Americans have stronger preferences for American and Japanese brands and against Chinese brands, and Chinese consumers have stronger preferences for German and American brands and against Japanese and South Korean brands.

4. Analysis

We use the estimated coefficients from model 3 to answer the three primary research questions posed in the introduction.

Q1: How do U.S. and Chinese preferences for vehicle attributes compare?

Since the coefficients from model 3 are difficult to interpret in the utility space, we transform them into a "willingness-to-pay" space by dividing each coefficient by the negative of the price coefficient (or $\exp(\beta_3)$ in the mixed logit model since it is distributed log-normally), which relates utility to dollars. Confidence intervals are computed by simulation. Note that the price coefficient is highly significant and negative, and there is no statistically significant difference between the two countries. It has been observed that respondent choices on hypothetical conjoint questions for high cost durables can be less sensitive to price than choices made with real money in the marketplace (Feit et al., 2010), so we expect these price coefficient estimates to be conservative.

When interpreting the results in terms of willingness-to-pay, it is important to keep in mind that we are comparing trade offs for incremental changes in vehicle attributes in an "all else being equal" world. For example, when examining vehicle type we are comparing a difference in preferences for two vehicles that are identical in every way except for powertrain type (e.g. a CV versus a HEV, with identical fuel economy, styling, operating cost, price, etc.). Figure 2 below summarizes the willingness-to-pay for each vehicle attribute described above. The error bars represent uncertainty in the mean estimates (heterogeneity in preferences is not shown).

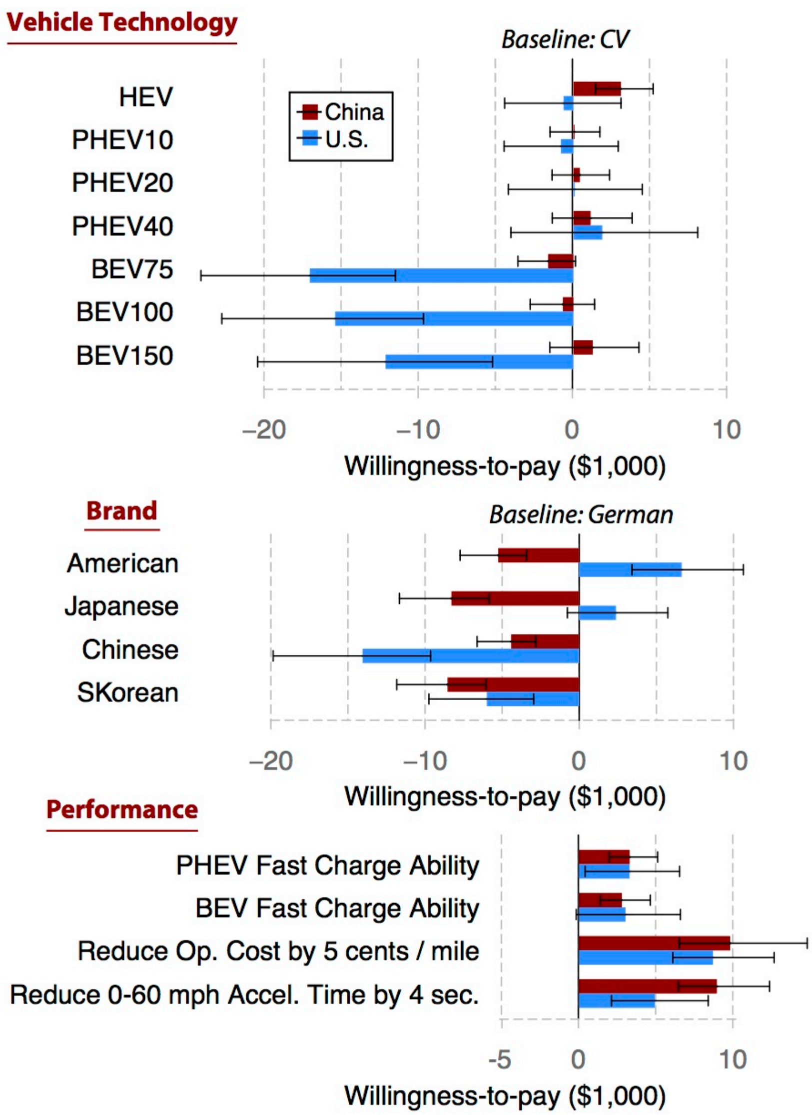

FIGURE 2 Willingness-to-pay for vehicle attributes in the China and the U.S. Error bars show uncertainty in the means.

We find that, all else being equal, Chinese respondents are willing to pay on average premiums of approximately $3,000 for HEV technology, while U.S. respondents are indifferent between HEVs and CVs. U.S. respondent willingness-to-pay drops by an average of $12,000–$17,000k for BEV technology with limited range – larger than what can be gained in fuel cost savings even if vehicle purchase prices were comparable. In contrast, Chinese consumer willingness-to-pay for BEV technology ranges from negative $2,000 to positive $2,000 relative to CVs, depending on the all-electric range (AER). We also find preferences for BEVs are heterogeneous, with a positive effect for as much as 3% to 88% of respondents in China, depending on AER.

Respondents in both countries are willing to pay premiums on average of $3,000 for the ability to fast charge a plug-in vehicle (both PHEVs and BEVs alike). This result holds across all models. Operating cost and acceleration time are both highly significant and robust to model specification, with consistent signs and orders of magnitude across all models. On average, Chinese and U.S. respondents are willing to pay similar premiums for a decrease in operating costs ($9,700 and $8,600 per $0.05/mile-reduced, respectively), but Chinese respondents are willing to pay more than U.S. respondents for a decrease in the 0 to 60 mph acceleration time ($9,000 and $5,000 per 4 second decrease, respectively).

Finally, all brand effects are highly significant with large sizes and large, statistically significant differences for each between the two countries. The brand ranking from most preferred to least preferred for the U.S. is: American, Japanese, German, S. Korean, and Chinese. For China the brand ranking is: German, Chinese, American, Japanese, and S. Korean. We calculate that on average Chinese respondents are willing to pay as much as $8,000 and U.S. respondents as much as $20,000 to move from the least preferred to the most preferred brands (S. Korean to German in China, and Chinese to American in the U.S.).

Q2: How would current plug-in vehicles compete against their conventional counterparts in the U.S. and China?

Consumer willingness to adopt plug-in vehicles will depend on the mix of attributes they are able to offer (type, range, acceleration, operation cost, price, etc.) – not just the vehicle type. To examine the implications of the model coefficients for combinations of attributes that current plug-in vehicles offer, we use model 3 to simulate market penetration of select models of currently available plug-in vehicles and their conventional counterparts, modeled as if they were the only two vehicles available in the market. We chose vehicles for which the body and general appearance are similar between different vehicle types (such as the Ford Focus BEV100 and Ford Focus CV) as this mimics how our survey was presented, and since choice models can predict share only when all attributes excluded from the model (including aesthetics) are identical across vehicle alternatives or have a negligible effect on choice. It is important to note that these share estimates reflect the expected outcome if every survey respondent selects one vehicle from the two vehicle options available in each case. Since the set of consumers who would consider the two vehicle models in practice is not a random subset of the respondents – and for other reasons such as model availability, advertising, incentives, etc. – observed share in the marketplace will differ. We hope to be able to compare the predicted share to those from the actual market in the near future, but are currently unable to do so as most of these vehicles are not yet available for sale in China and are only available in relatively small numbers in the U.S.

We made comparisons between six pairs of vehicles: two comparing PHEVs to HEVs, two comparing PHEVs to CVs, and two comparing BEVs to CVs. We find that the HEVs are preferred to the PHEVs in both countries by similar margins. The Chevrolet Cruze Eco (a CV) is highly preferred over its PHEV40 counterpart (the Volt) in both countries while the opposite is true for the BYD PHEV40 compared to its CV counterpart. This difference is largely because the Cruze Eco has relatively good operating cost (or fuel economy) compared to the Volt, but the Volt is more than double in price. For the BYD case, the PHEV40 is also much more expensive than it's CV counterpart, but also is over three times better in operating cost. Finally, we find that pure electric BEVs compete poorly against their CV counterparts in both countries, although the expected share in China is still sizeable (about 25% share), suggesting Chinese respondents would be more willing to adopt BEVs. Figure 3 below summarizes the simulated share breakdown.

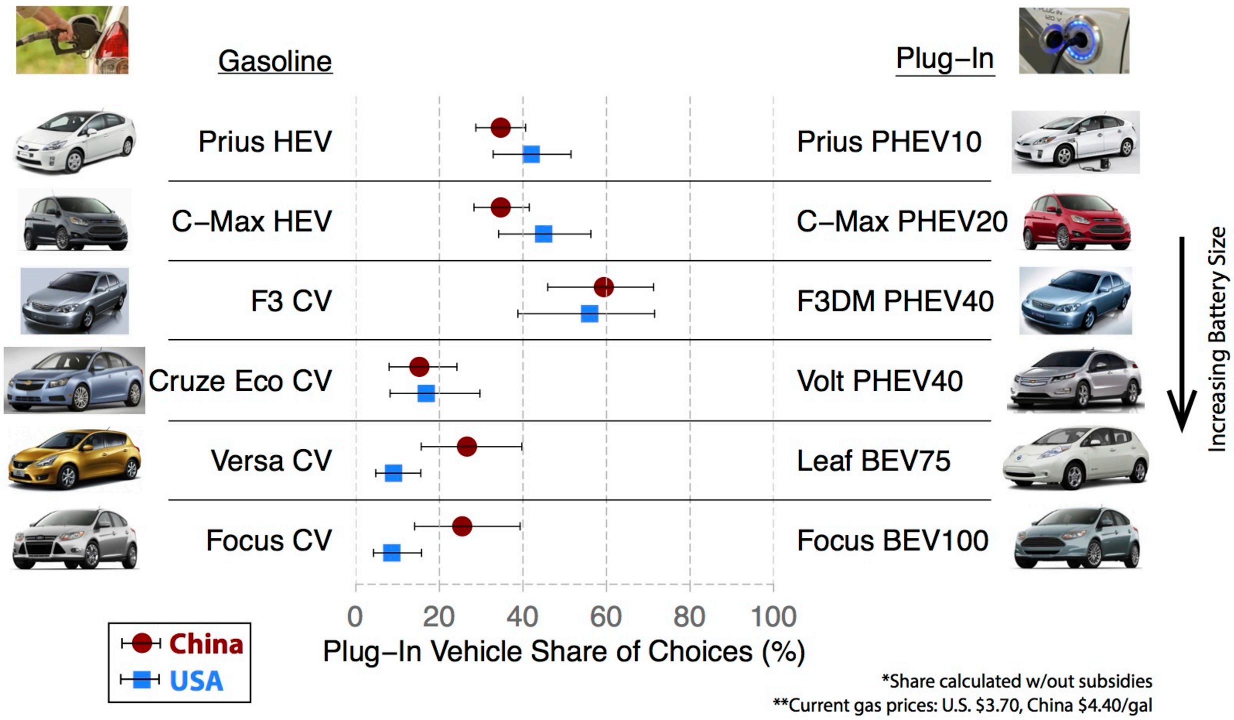

FIGURE 3 Predicted share of survey respondent choices for select plug-in vehicles and their gasoline counterparts.

Q3: Under what conditions would the average car buyer be indifferent between a gas car and its plug-in counterpart?

For the same pairs of vehicles, we calculate two conditions that would shift the share of choices between plug-in and gasoline vehicles to 50%, making the average consumer indifferent between choices: 1) the desired subsidy (or reduction in price) for the plug-in vehicle, and 2) the required price of gasoline. Table 5 shows the results of these calculations for different vehicle technologies with and without the currently offered federal subsidies in the U.S. and China. We observe that in both countries the desired subsidies are all positive, meaning the prices of all plug-in vehicles examined are too high without any subsidies for consumer indifference. In the U.S., the currently offered subsidy is sufficient to “close the gap” to achieve indifference for smaller battery PHEVs, but for larger battery BEVs the subsidies would need to increase by an additional $15,000 on top of the currently offered maximum subsidy of $7,500 to achieve indifference. We see the opposite situation in China; the current maximum subsidy of approximately $9,500 is more than enough to achieve indifference for larger battery BEVs, but the subsidy offered for smaller battery PHEVs is too small to meet the desired subsidies to achieve indifference. The same observations are true when considering the price of gasoline instead of desired subsidies.

TABLE 5
Required conditions for survey respondent choice indifference between plug-in vehicles and gasoline counterparts

What subsidy is needed for indifference between a plug-in vehicle and it's conventional counterpart?

		USA		China	
Battery Size	Technology	Subsidy Desired for Indifference	Subsidy Currently Offered	Subsidy Desired for Indifference	Subsidy Currently Offered
Small	PHEV10	\$3,400 ± \$600	\$3,000	\$6,800 ± \$1,400	\$2,400
	PHEV20	\$2,000 ± \$1,700	\$4,000	\$6,400 ± \$1,300	\$3,500
Medium	PHEV40	\$15,500 ± \$7,000	\$7,500	\$16,500 ± \$2,600	\$7,600
Large	BEV75	\$22,600 ± \$1,200	\$7,500	\$6,600 ± \$1,600	\$9,400
	BEV100	\$22,400 ± \$200	\$7,500	\$6,100 ± \$900	\$9,500

What price of gasoline is needed for indifference between a plug-in vehicle and it's conventional counterpart?

		USA		China	
Battery Size	Technology	Price with No Subsidies	Price With Current Subsidies	Price with No Subsidies	Price With Current Subsidies
Small	PHEV10	\$6.10 ± \$0.40	\$4.00	\$9.50 ± \$1.00	\$7.70
	PHEV20	\$4.80 ± \$0.90	\$2.60	\$8.20 ± \$0.80	\$6.10
Medium	PHEV40	\$14.70 ± \$5.00	\$9.40	\$16.70 ± \$1.90	\$11.10
Large	BEV75	\$9.40 ± \$0.40	\$7.50	\$6.20 ± \$0.40	\$3.50
	BEV100	\$9.30 ± \$0.10	\$7.50	\$6.00 ± \$0.20	\$3.70

*Current gas prices: U.S. = \$3.70, China = \$4.40

Figure 4 below presents the same results as in Table 5, except we plot the desired subsidy against the battery capacity of the plug-in vehicle to compare them against the currently available subsidies in both countries, which scales with battery capacity. Here it is easier to visualize the relationship between consumer preferences (in the form of a desired subsidy to achieve indifference) and current subsidy policies in the U.S. and China. Again, in the U.S. we observe significant barriers to BEV adoption and relatively low barriers to PHEV adoption. This holds both with and without the currently available federal subsidies. In China, we observe that the desired subsidy is relatively independent of battery capacity, but the current subsidy scheme makes BEVs more attractive than PHEVs. Note that the BYD F3 is not plotted on the figure because it’s desired subsidy would be below zero (i.e. you would need to increase its price rather than lower it to make the average consumer indifferent).

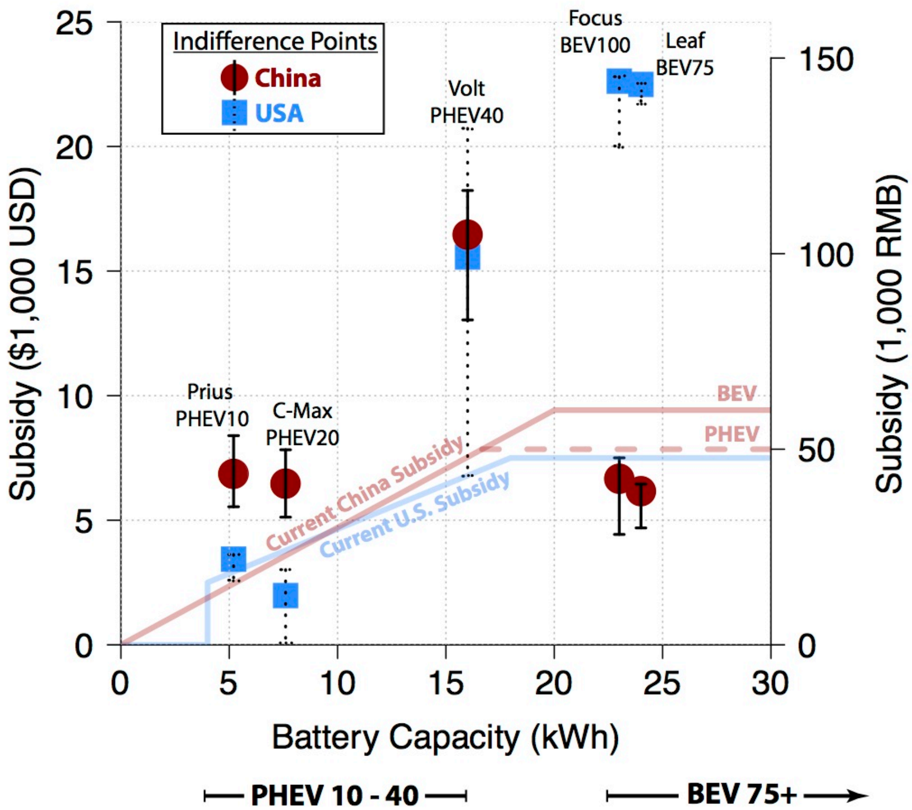

FIGURE 4 Indifference points for select plug-in and non-plug-in vehicle pairs in China and the U.S.

5. Conclusions and Policy Implications

Vehicle electrification is one of the most promising near-term alternatives for achieving reduction in oil consumption and harmful emissions from passenger cars. This work aims to understand what factors affect consumer preferences for emerging hybrid and electric vehicle technologies in the U.S. and China and how much each factor contributes to consumer choices. Our choice-based conjoint experiment results suggest that Chinese consumers prefer HEV powertrains relative to CVs, and that both Chinese and U.S. consumers dislike BEV powertrains relative to CVs, all else being equal. We find Chinese consumers are more willing to adopt BEVs than U.S. consumers and that U.S. consumers are on average less sensitive to acceleration time. We find that consumers in both countries are willing to pay significant premiums for the ability to fast charge a plug-in vehicle (both PHEVs and BEVs alike). We find that operating cost is one of the most important factors influencing consumer choice, a finding consistent with previous work (Boyd & Mellman, 1980), (Brownstone & Train, 1999). We also find that AER is not a significant factor influencing choice for PHEVs in both countries, a finding (Axsen & Kurani, 2010) previously identified for the U.S. Finally, we find that brand is highly influential for car buyers, particularly in China, and the effect from least to most preferred brand in both countries is higher than any effect from vehicle type (HEV, PHEV, BEV, or CV).

The barriers to adoption for BEVs and PHEVs involve both consumer preferences and policy in both countries. In the U.S., trends in consumer preferences towards HEVs and PHEVs and against BEVs hold independent of current subsidies. In China, the subsidies have a more significant influence, making BEVs more attractive than PHEVs. Previous research suggests that in the U.S., HEVs and small-battery PHEVs have more emission and oil displacement benefits on average than large-battery BEVs (Michalek et al., 2011). While U.S. consumer preferences are well aligned with these benefits, U.S. policy is misaligned with benefits. In China, research suggests that HEVs on average have a higher potential to reduce energy consumption and, depending on grid mix, a higher potential to reuduce emissions than BEVs (Lang et al., 2013). Chinese consumers have less of a strong preference for HEVs and PHEVs over BEVs, but current subsidies shift consumer willingness to adopt towards BEVs, which is misaligned with energy and environmental benefits.

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