Demand for Battery-electric & Plug-in Hybrid Vehicles: Policy Lessons for an Emerging Market

Tamara L. Sheldon*[1], J.R. DeShazo†[2], and Richard T. Carson‡[3]

[1]Department of Economics, University of South Carolina
[2]Luskin School of Public Affairs, University of California, Los Angeles
[3]Department of Economics, University of California, San Diego

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Abstract Understanding demand in the new plug-in hybrid electric vehicle (PHEV) market is critical to designing more effective adoption policies. We use stated preference data from an innovative choice experiment to estimate demand for PHEVs relative to battery electric vehicles (BEVs) and to explore heterogeneity in demand for these vehicle technologies. We find that the gap between willingness to pay for PHEVs and their price premium over conventional vehicles is on the order of current subsidies, while that of BEVs is an order of magnitude larger. We also find evidence that consumers with access to HOV lanes are more likely to purchase PHEVs and that the characteristics of the home charging environment are more important for BEV purchase decisions. Finally, we use a latent class model to show that PHEVs draw an entirely new consumer segment into the electric vehicle market that would not consider purchasing a BEV.

*Tamara.Sheldon@moore.sc.edu
†deshazo@ucla.edu
‡rcarson@ucsd.edu

1 Introduction

Policymakers have sought to spur demand for plug-in electric vehicles (PEVs) through a variety of policy incentives. The economic rationale for the design of these policy incentives has been based on the presence and size of environmental and knowledge-spillover externalities. The desired effect of policies targeting these externalities is to adjust consumers' *ex post* demand for these vehicles in ways that enhance overall social welfare. However, understanding of consumer demand for these vehicles and associated interactions with policy incentives is incomplete because automakers have recently differentiated their plug-in electric vehicle product mix.

Automakers have added plug-in hybrid electric vehicles (PHEVs), which may be fueled by either electricity or gasoline, to the early mix of battery electric vehicles (BEVs), which are fueled only by electricity. By adding PHEVs, automakers sought to eliminate consumers' "range anxiety" associated with the limited travel range of smaller-battery BEVs. PHEVs also represented a vehicle design innovation that enabled many automakers to adapt pre-existing vehicle designs to plug-in electric refueling, thus eliminating their need to design entirely new models. For instance, there are now PEV versions of the Ford Fusion and Honda Accord, as well as the Mitsubishi Outlander and the Porsche Panamera. The attractiveness of the PHEVs relative to BEVs to automakers has been revealed by the decision to introduce a substantial number of PHEVs to the market (see Table 1) with plans for many more in the relatively near future as rumored in the trade press (e.g., the Audi A3 e-tron and the Hyundai Sonata Plug-in). Consumers have thus far exhibited a preference for PHEVs relative to BEVs by purchasing relatively more of them, as shown Figure 1.

Within the literature, researchers have undertaken innovative studies of consumer demand for BEVs (Bunch et al., 1993; Brownstone, Bunch, and Train, 2000; Hidrue et al., 2011), however, research on PHEV demand remains limited. Most existing research studies were implemented before PHEVs were commercially available and they focused on design priorities for vehicle attributes (Kurani, Heffner, and Turrentine, 2008; Axsen and Kurani,

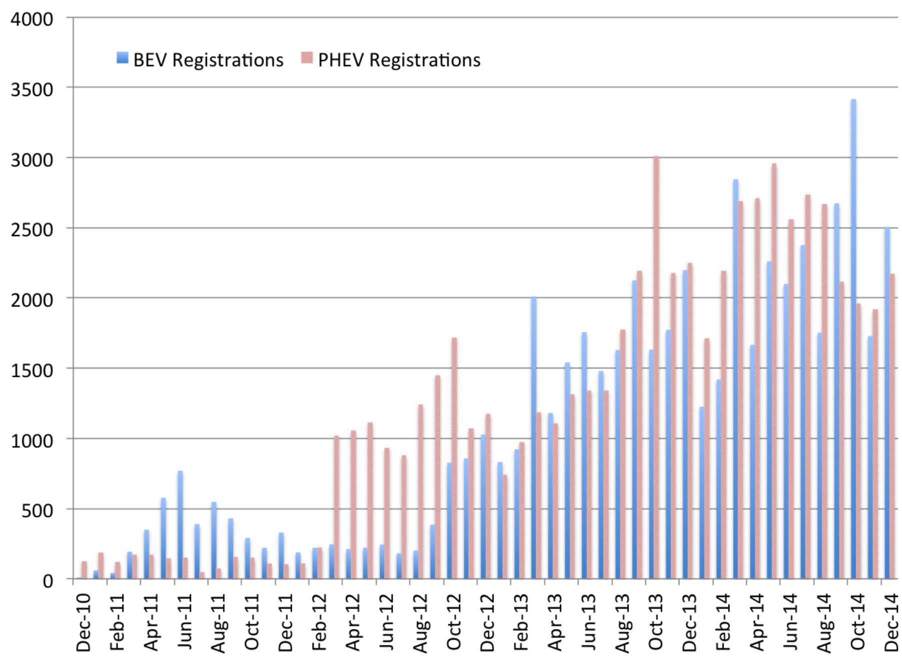
2009) as well as qualitative market trial studies (Caperello and Kurani, 2012; Graham-Rowe et al., 2012).

Table 1: PEV Model Introductions

2012-2013			2014-2015		
Model	Make	PEV Type	Model	Make	PEV Type
Model S Variations	Tesla	BEV	i3	BMW	BEV
2012 smart fortwo ed.	Daimler	BEV	E-Golf	VW	BEV
e6	BYD	BEV	i8	BMW	PHEV
Chevy Spark	GM	BEV	Cayenne S E-Hybrid	Porsche	PHEV
Scion iQ	Toyota	BEV	918 Spyder	Porsche	PHEV
RAV4 EV	Toyota	BEV	Soul EV	Kia	BEV
C-Max Energi	Ford	PHEV	B-Class Electric	Mercedes-Benz	BEV
Fusion Energy	Ford	PHEV	A3 e-tron	Audi	PHEV
Fit EV	Honda	BEV	Infinity LE	Nissan	BEV
GCE	Amp	BEV	Model X	Tesla	BEV
MLe	Amp	BEV	A3 e-tron	Audi	PHEV
Accord PHV	Honda	PHEV	Golf twinDRIVE	VW	PHEV
F3DM	BYD	PHEV	Sonata Plug-in Hybrid	Hyundai	PHEV
F6DM	BYD	PHEV	Outlander Sport PHV	Mitsubishi	PHEV
500 Elettrica	Chrysler-Fiat	BEV	A4 e-quattro	Audi	PHEV
Cadillac ELR	GM	PHEV	V60 Plug-in Hybrid	Volvo	PHEV
Prius Plug-in Hybrid	Toyota	PHEV			
Panamera	Porsche	PHEV			
Focus Electric	Ford	BEV			

Closest to our work here is Axsen and Kurani (2013), who survey a sample of recent new car buyers in San Diego who are asked to play a design game where they get to assemble vehicles by allocating points to different attribute options. They find that PEVs are preferred to regular hybrids, which in turn are preferred to regular vehicles. PHEVs dominate BEVs. An important finding from this study is that PHEVs with shorter ranges may be more

Figure 1: PEV Registrations in California by Month



commercially viable than more expensive longer-ranged PHEVs.[1]

1.1 Understanding Demand to Guide Policy Design

Several important questions relevant to understanding the need for, and design of, public policies remain unanswered. A critical empirical question is how large are the differences in consumer demand for BEVs, PHEVs and internal combustion engines (ICEs), *ceteris paribus*? Answering this question helps us to understand the magnitude of importance of the PHEV as a vehicle innovation in the growth of the plug-in electric vehicle market. This relative preference information is also critical in determining whether vehicle purchase incentives will even be needed to encourage PHEV purchases, and if so, how effective they are likely to be in compensating for utility differentials across types of vehicles. Lastly, understanding

[1]This study in some ways can be seen as the inverse of ours. We focus on prospective new car buyers in California at a time when a substantial number of PHEVs and BEVs have already been introduced and look at choices between competing vehicles that are described by attributes rather than having recent buyers assemble preferred vehicle configurations from sets of attributes.

utility differentials enables economists to evaluate the size of "free rider" losses associated with vehicle purchase incentives for BEVs versus PHEVs, as well as the aggregate public revenues needed to support these rebate policies.[2]

Beyond vehicle purchase incentives, there are also important questions about how differences in consumer demand for BEVs and PHEVs interact with other public policy incentives. For example, some researchers have suggested that demand for BEVs, relative to PHEVs, may be more sensitive to the presence of residential and publicly-accessible recharging infrastructure since BEVs cannot operate using gasoline (Egbue and Long, 2012; Khan and Kockelman, 2012). If true, this might explain how the policy provision for charging infrastructure and PEV-friendly buildings will affect the relative rates of purchase of BEVs and PHEVs. In addition, many states allow BEVs and PHEVs to use high occupancy vehicle (HOV) lanes. When predicting PEV market growth impacts, it may be useful to policymakers to better understand if there are differences in how HOV access induces demand for BEVs versus PHEVs.

Better understanding consumer valuation of PHEVs and their attributes can also inform us of how this new market is likely to evolve as newer vehicle models come to market. For example, estimating consumer preferences for PHEV range can help in understanding how consumer demand will likely respond to second generation, extended-range PHEVs that are expected to be available in the next several years.

1.2 Demand Modeling Strategy

Using stated preference data from a survey of California new car buyers, we estimate discrete choice models that allow us to compare demand for BEVs, PHEVs, and conventional ICE vehicles. Not only is this one of the first studies to investigate relative demand for

[2]DeShazo, Sheldon, and Carson (2015) find that rebates are more cost-effective not only when they target consumer segments with more marginal consumers, but also when they target segments with fewer infra-marginal consumers. For example, they find that it is optimal to allocate higher rebates to BEV purchases than to PHEV purchases since there are more infra-marginal PHEV purchasers who receive the rebate and who would have purchased the PHEV even in the absence of the rebate.

different PEV technologies, but our analysis also utilizes innovative experimental design techniques, including a Bayesian D-efficient design that enables a more efficient estimation, as well as a pivoting on current preference and prices for non-PEV vehicles in order to make the choices faced by survey respondents more realistic.

We estimate three models that allow us to explore heterogeneity of preferences for PEVs from several angles. First, we estimate a mixed logit model that allows for the estimated preference parameters to randomly vary. Second, we estimate an alternative specific constant logit, which provides insight into what consumer characteristics tend to be associated with different aspects of the preference parameter distributions. Finally, we estimate a latent class model, which allows us to uncover customer profiles of market segmentation.

2 Survey Design and Data

We administered an online survey to a representative sample of Californian new car buyers and obtained a sample of 1,261 completed surveys.[3] The survey first gathered household, vehicle, and demographic data. Next, the survey elicited body and brand preferences. Respondents were asked to choose the top two vehicle body types (out of twelve options) they were most likely to select for their next new vehicle purchase, as shown in Figure 2. Then respondents were asked to select the top three brands (out of the twenty most popular brands by sales volume in California in 2012) they were most likely to select for their next new vehicle purchase, as shown in Figure 3.

Next, respondents were shown four sets of five vehicles, as shown in Figure 4, and in each set were asked to choose which of the five vehicles they were most likely to select for their next new vehicle purchase. The total set of twenty vehicles respondents chose from included all conventional vehicles (including internal combustion engine vehicles, hybrid electric vehicles, and diesel-fueled vehicles) on the new vehicle market as of the fall of 2013

[3]Of the respondents who completed an initial screener, approximately 42% both qualified as potential new car buyers and completed the survey.

that are of both the top brand and top body selected by respondents. The remainder of the twenty included a random draw of vehicles that are of the top body choice and second or third brand choice, or of the second body choice and top brand choice. In cases where the set of vehicles that meets these criteria is less than twenty, the remainder of the vehicles were a random selection of vehicles that are of either one of the top body selections or of the top brand selections. Finally, respondents were asked to choose which one of the four vehicles chosen as top picks out of the twenty vehicles in the previous five questions they would be most likely to select for their next new vehicle purchase, as shown in Figure 5. This 'top' vehicle and its characteristics are carried through to subsequent questions in the survey.

Figure 2: New Car Buyer Survey: Body Choice

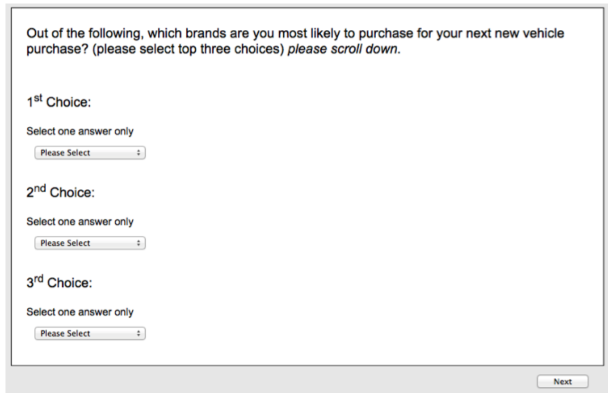
Respondents were provided with information on BEV and PHEV technologies and introduced to PEV attributes, including refuel price, electric range, and HOV lane access. Finally, respondents were asked to choose between the conventional version, two BEV versions, and two PHEV versions of the vehicle they previously indicated as their top choice. In each choice set the first column displayed the conventional vehicle, and we randomized whether the two BEVs or PHEVs appeared in the subsequent columns. Attribute levels vary for each vehicle version as shown in Table 2, with price pivoting off the price of the existing conventional vehicle. An example choice set is shown in Figure 6. By choosing between five versions of the top vehicle, respondents are encouraged to assume that everything else (e.g., trim and performance) except the listed attributes are identical. This allows us to focus on how respondents make tradeoffs between vehicle technology, price, refuel cost, electric range, and HOV lane access.

We use NGENE software to design the choice experiment. We sought an experimental design to minimize the variance of the estimated coefficients of the specified utility function that underlies the logit models. The efficiency of an experimental design can be greatly improved if we know the approximate magnitude or even just the sign of the true parameters (Scarpa and Rose, 2008). For example, by assuming that the coefficient on price is negative, or that consumer utility for an alternative is reduced as that alternative gets more expensive, we no longer need an experimental design that can distinguish between a negative or positive coefficient, but can instead more precisely estimate a negative coefficient.

Specifically, we use an algorithm in NGENE that allows us to maximize the amount of information we are able to extract from our choice experiment by minimizing the variance-covariance estimator of the vector of utility function coefficients. The algorithm searches through potential experimental designs with different combinations and levels of attributes. We select the experimental design with the smallest determinant of the asymptotic variance-covariance matrix, also known as the D-error.[4] To further increase the efficiency of the

[4]For more details see Scarpa and Rose (2008).

Figure 3: New Car Buyer Survey: Brand Choice



Out of the following, which brands are you most likely to purchase for your next new vehicle purchase? (please select top three choices) *please scroll down.*

1st Choice:

Select one answer only

Please Select

2nd Choice:

Select one answer only

Please Select

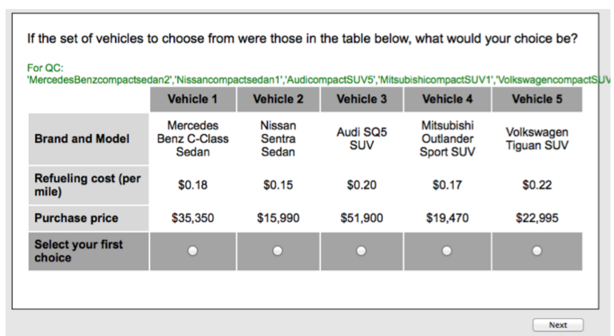
3rd Choice:

Select one answer only

Please Select

Next

Figure 4: New Car Buyer Survey: Top Vehicle Choice



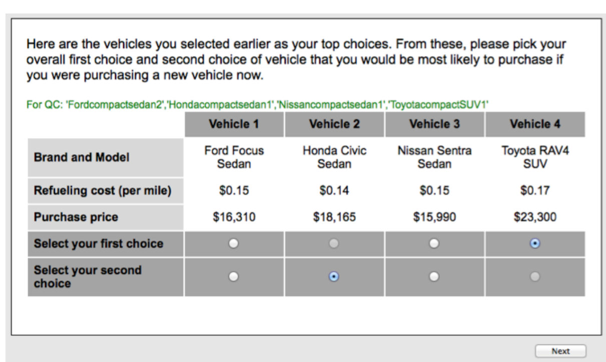
If the set of vehicles to choose from were those in the table below, what would your choice be?

For QC: 'MercedesBenzcompactsedan2','Nissancompactsedan1','AudicompactSUV5','MitsubishicompactSUV1','VolkswagencompactSUV

	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4	Vehicle 5
Brand and Model	Mercedes Benz C-Class Sedan	Nissan Sentra Sedan	Audi SQ5 SUV	Mitsubishi Outlander Sport SUV	Volkswagen Tiguan SUV
Refueling cost (per mile)	$0.18	$0.15	$0.20	$0.17	$0.22
Purchase price	$35,350	$15,990	$51,900	$19,470	$22,995
Select your first choice					

Next

Figure 5: New Car Buyer Survey: Top Vehicle Choice



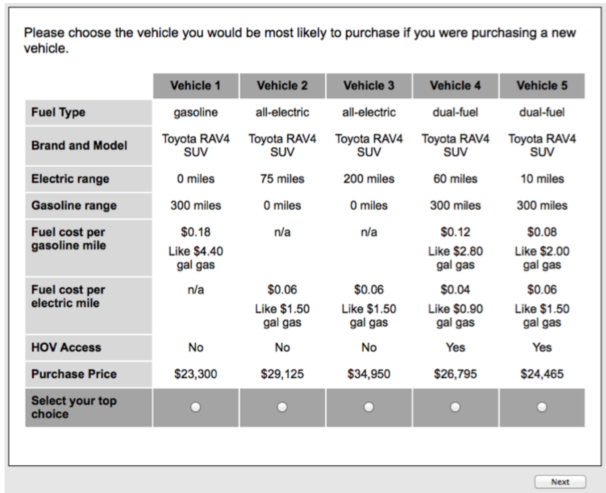
Here are the vehicles you selected earlier as your top choices. From these, please pick your overall first choice and second choice of vehicle that you would be most likely to purchase if you were purchasing a new vehicle now.

For QC: 'Fordcompactsedan2','Hondacompactsedan1','Nissancompactsedan1','ToyotacompactSUV1'

	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4
Brand and Model	Ford Focus Sedan	Honda Civic Sedan	Nissan Sentra Sedan	Toyota RAV4 SUV
Refueling cost (per mile)	$0.15	$0.14	$0.15	$0.17
Purchase price	$16,310	$18,165	$15,990	$23,300
Select your first choice				
Select your second choice				

Next

Figure 6: New Car Buyer Survey: PEV vs. Conventional Vehicle Choice Module


Please choose the vehicle you would be most likely to purchase if you were purchasing a new vehicle.

	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4	Vehicle 5
Fuel Type	gasoline	all-electric	all-electric	dual-fuel	dual-fuel
Brand and Model	Toyota RAV4 SUV	Toyota RAV4 SUV	Toyota RAV4 SUV	Toyota RAV4 SUV	Toyota RAV4 SUV
Electric range	0 miles	75 miles	200 miles	60 miles	10 miles
Gasoline range	300 miles	0 miles	0 miles	300 miles	300 miles
Fuel cost per gasoline mile	$0.18 Like $4.40 gal gas	n/a	n/a	$0.12 Like $2.80 gal gas	$0.08 Like $2.00 gal gas
Fuel cost per electric mile	n/a	$0.06 Like $1.50 gal gas	$0.06 Like $1.50 gal gas	$0.04 Like $0.90 gal gas	$0.06 Like $1.50 gal gas
HOV Access	No	No	No	Yes	Yes
Purchase Price	$23,300	$29,125	$34,950	$26,795	$24,465
Select your top choice					

Next

design, we specify Bayesian priors. That is, for each coefficient that we seek to estimate, we specify an assumed *a priori* distribution. We base these assumptions on parameter estimates from earlier studies looking at PEV attributes (Bunch et al., 1993; Golob et al., 1993; Brownstone, Bunch, and Train, 2000; Ewing and Sarigöllü, 2000; Hidrue et al., 2011; Qian and Soopramanien, 2011; Achtnicht, Bühler, and Hermeling, 2012).

To make the choice experiment more realistic for respondents, we employ a pivot design. Price levels are designed to be percentages of a reference value. The price of the top conventional vehicle chosen by a respondent becomes her reference price, and the different price levels she sees are the percentage levels as specified by the experimental design multiplied by the reference price. For example, a respondent who selects a conventional model that costs $30,000 would see BEV and PHEV versions of that model that cost $31,500, $34,500, $37,500, or $45,000. On the other hand, a respondent who is considering the luxury end of the market and selects a conventional model that costs $60,000 would see BEV and PHEV versions of that model that cost $63,000, $69,000, $75,000, or $90,000.

To incorporate the pivoting price attribute levels in the experimental design, NGENE's algorithm uses relative attribute levels rather than absolute attribute levels for price. How-

Table 2: Attribute Levels

Purchase Price[1] (% of conventional)	
Gasoline	100%
BEV	105%, 115%, 125%, 150%
PHEV	105%, 115%, 125%, 150%
Gasoline Refuel Cost ($ per gal)	
Gasoline[2]	$4.00, $4.40, $4.80, $5.60
BEV	n/a
PHEV[3]	$2.00, $2.20, $2.40, $2.80
Electric Refuel Cost[4] ($ per gal equivalent)	
Gasoline	n/a
BEV	$0.90, $1.10, $1.50, $2.50
PHEV	$0.90, $1.10, $1.50, $2.50
Gasoline Range (miles)	
Gasoline	300
BEV	300
PHEV	0
Electric Range (miles)	
Gasoline	n/a
BEV	50, 75, 100, 200
PHEV	10, 20, 40, 60
HOV Access	
Gasoline	no
BEV	no, yes
PHEV	no, yes

[1] The respondent sees price in dollars. For example, a respondent who selected a conventional model that costs $30,000 would see BEV and PHEV versions of that model that cost $31,500, $34,500, $37,500, or $45,000.
[2] At the time the survey was administered, average gasoline cost in California was approximately $4 per gallon.
[3] The average gasoline fuel economy of PHEVs as of December 2013 was 41mpg, which is roughly double the fuel economy of our gasoline vehicle universe of 20mpg. Therefore we choose a baseline gasoline refueling cost for PHEVs that is half that of gasoline vehicles.
[4] At the time the survey was administered, the average overnight electricity rate in California was roughly 16 cents per kWh and the average vehicle economy of electric vehicles was 3.5 miles per kWh, suggesting an average cost per electric mile of $0.046. The average cost per mile of gasoline vehicles in our vehicle universe is $\frac{\$4/gal}{20mi/gal} = \$0.20$ per mile. Thus on average, refueling cost for electric miles is 23% of the $4 per gallon refueling cost for gasoline miles, or $0.92/gal. Therefore we choose a baseline electric refueling cost of $0.90 per gallon equivalent.

ever, in calculating the efficiency of the design, the algorithm must assume some reference level. Therefore, we assume four different segments: 1) economy and compact cars, 2) mid-size and large cars, 3) SUVs, trucks, and minivans, and 4) luxury vehicles. For each segment we assume the price is the average of that vehicle type from the new vehicle universe. The algorithm utilizes a model averaging approach according to the actual market shares of the four segments.

Table A.1 in the Appendix gives definitions of all the variables used in our analysis. Most of these variables were collected in the survey. We obtained average gasoline prices in December 2013 by Census Tract from Gas Buddy Organization Inc. From the U.S. Department of Energy's Alternative Fuels Data Center we obtained a measure of publicly-available PEV charger density, which we define as the number of level 2 chargers within a 5-mile radius of the population centroid of a Census Tract as of December 2013.

3 Model Specification

The standard multinomial logit can model the probability of selecting a vehicle over other alternatives. In this model, a respondent selects the vehicle that gives her greater utility than any other available alternative. The utility of each alternative is a function of its attributes. The estimated coefficients tell us how a change in each attribute (e.g., an increase in range) impacts utility.

Individual n receives utility U_{ni} from choosing alternative i:

$$U_{ni} = V_{ni} + \varepsilon_{ni}. \tag{1}$$

The probability of individual n selecting alternative i is the probability her utility from i is greater than her utility from choosing any other available alternative:

$$\pi_{ni} = Prob\left(V_{ni} + \varepsilon_{ni} \geq V_{nj} + \varepsilon_{nj}\right); \forall j \neq i. \tag{2}$$

If we assume ε_{ni}'s are independently distributed Type-I extreme value errors and a linear utility function, such that $V_{ni} = \mathbf{x_i}'\boldsymbol{\beta}$, where $\mathbf{x_i}$ is a vector of attributes of i and $\boldsymbol{\beta}$ is a vector of parameters, then we can model the probability of individual n choosing alternative i as:

$$\pi_{ni} = \frac{exp(\mu_n \mathbf{x_i}'\boldsymbol{\beta})}{\sum_{j=1}^{J} exp(\mu_n \mathbf{x_j}'\boldsymbol{\beta})}, \tag{3}$$

where μ_n is a scale parameter commonly assumed to equal 1.

In this model, the coefficients are fixed, effectively assuming that all respondents have the same preferences (e.g., all respondents have the same value for a BEV, all else being equal). The logit model exhibits the independence of irrelevant alternatives (IIA), meaning that the odds of choosing vehicle j over vehicle k are independent of the choice set for all pairs j, k, which may imply unrealistic substitution patterns. The standard logit model does not allow for heterogeneity of preferences.

The first model we estimate that relaxes this assumption is a mixed logit. In the mixed logit model, developed by Train (1998), the coefficients of the utility function are random parameters for which we can specify a distribution. For example, if we assume a coefficient is normally distributed, we estimate both the mean and standard deviation of that coefficient. This model allows for heterogeneous preferences across respondents and does not necessarily exhibit the IIA property, thereby allowing for more flexible substitution patterns. Structurally, the mixed logit model is similar to the standard logit except the parameters of the utility function are assumed to be random, not fixed, and the probability of individual n selecting alternative i becomes:

$$\pi_{ni} = \int \frac{exp(\mu_n \mathbf{x_i}'\boldsymbol{\beta})}{\sum_{j=1}^{J} exp(\mu_n \mathbf{x_j}'\boldsymbol{\beta})} f(\boldsymbol{\beta}|\boldsymbol{\theta}) \partial \boldsymbol{\beta}, \tag{4}$$

where $f(\boldsymbol{\beta}|\boldsymbol{\theta})$ is the density function of $\boldsymbol{\beta}$.

A drawback of the mixed logit model is that it does not tell us where different respondents are in the estimated distribution of preferences.[5] In other words, it does not tell us which respondents have which preferences.

The alternative specific constant (ASC) logit and the latent class logit offer two different methods of further exploring heterogeneity. The ASC logit, developed by McFadden (1974), is a constant parameter logit where explanatory variables in the utility function include not only alternative attributes but also respondent characteristics. The ASC logit estimation therefore tells us how respondent characteristics impact their odds of selecting a BEV or PHEV relative to the gasoline version. The ASC logit is similar to the standard logit except the utility function includes consumer characteristics:

$$V_{ni} = \mathbf{x_i'}\boldsymbol{\beta} + \mathbf{z_n'}\boldsymbol{\gamma}, \tag{5}$$

where $\mathbf{z_n}$ is a vector of characteristics of individual n and $\boldsymbol{\gamma}$ is a vector of parameters.

The latent class model is similar to the ASC logit model in that preferences are heterogeneous across respondents characteristics. The latent class model segments the population into different classes, where preferences for each class are estimated separately, and class membership of respondents is determined by their characteristics.

Assume existence of S segments in a population. The probability of consumer n choosing alternative i conditional on membership in segment s, where s=1,..,S, is:

$$\pi_{ni|s} = \frac{exp(\mathbf{x_i'}\boldsymbol{\beta_s})}{\sum\limits_{j=1}^{J} exp(\mathbf{x_j'}\boldsymbol{\beta_s})}. \tag{6}$$

Allowing latent membership for segmentation to be:

$$M^*_{ns} = \mathbf{y_n'}\boldsymbol{\lambda_s} + \zeta_{ns}, \tag{7}$$

[5]Technically, it is possible to make the mean or variance of a mixed logit parameter a function of observed covariates, but in practice this is rarely done to problems because such models tend to be numerically unstable and frequently do not converge to a well-defined maximum value.

where

M^*_{ns}: membership likelihood function for individual n to be in segment s

$\mathbf{y_n}$: vector of both psychometric constructs and socioeconomic characteristics

$\boldsymbol{\lambda_s}$: vectors of parameters

ζ_{ns}: independently distributed Type-I extreme value errors

we can model the probability of consumer n belonging to segment s as:

$$\pi_{ns} = \frac{exp(\mathbf{y'_n}\boldsymbol{\lambda_s})}{\sum_{s=1}^{S} exp(\mathbf{y'_n}\boldsymbol{\lambda_s})}. \tag{8}$$

The probability of consumer n choosing alternative i is the the sum across segments of the probability of her selecting alternative i conditional on segment membership times her probability of segment membership:

$$\pi_{ni} = \sum_{s=1}^{S} \pi_{ns}\pi_{ni|s} \tag{9}$$

$$\pi_{ni} = \sum_{s=1}^{S} \frac{exp(\mathbf{y'_n}\boldsymbol{\lambda_s})}{\sum_{s=1}^{S} exp(\mathbf{y'_n}\boldsymbol{\lambda_s})} \frac{exp(\mu_s \mathbf{x'_i}\boldsymbol{\beta_s})}{\sum_{j=1}^{J} exp(\mu_s \mathbf{x'_j}\boldsymbol{\beta_s})}. \tag{10}$$

4 Results

4.1 Mixed Logit Model

Table 3 shows the results of the mixed logit estimation. The first two columns are estimated assuming that the price coefficient is normally distributed. The second two columns assume the price coefficient is log normally distributed.[6] Specifications with log normally dis-

[6]A log-normal distribution assumption for a parameter implies the coefficient should be positive. Therefore, we transform price, multiplying it by -1 for the estimation, and transform the resulting positive

tributed price coefficients have a better model fit. This is unsurprising since the log normal distribution allows for the mean to be greater than the median, which might be the case if some respondents are very price sensitive. Table 3 shows that on average (and all else being equal), respondents have a negative preference for BEVs relative to conventional gasoline vehicles (the omitted category), a positive preference for PHEVs, a positive preference for increased range and HOV access, and a negative preference for higher refueling costs.

Figure 7 shows kernel density plots of individual respondents' estimated coefficients, using a sampling method from Revelt and Train (2000). The distribution of the (negative) price coefficient appears to be log normal, as shown in Figure 7a. The median price coefficient is around 0.3 and the mean is substantially higher, suggesting a sizable fraction of respondents are very price sensitive.

Figure 7b shows that the distribution of coefficients for BEVs is bi- or perhaps even trimodal. While most respondents have a negative coefficient for BEVs of around -2, a small portion of the population has a positive preference for BEVs, and a significant portion of the population has an even stronger dislike of BEVs. Similarly, Figure 7c shows that the distribution of coefficients for PHEVs is bi-modal, with a minority of respondents having a coefficient around -2, but a majority of respondents having a strong positive preference for PHEVs with a coefficient closer to 4.

While range has a positive coefficient for all respondents, the distribution of the range coefficient as shown in Figure 7b also exhibits bi-modality, with some respondents caring significantly more than others, perhaps due to different commute distances.

Figure 7e shows that a minority of respondents does not seem to care about refueling costs, with a coefficient of zero, but that a majority of respondents do care about refueling costs, with a coefficient around -2. Similarly, Figure 7f shows that a large majority of respondents value HOV lane access, but a minority does not, which may reflect a lack of local HOV lane access.

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coefficient back post-estimation, multiplying by -1. Therefore, the price coefficient for the log-normal specification shown in Table 3 is negative.

Table 4 shows the mean estimates of willingness to pay (WTP) for vehicle attributes obtained using the Hensher and Greene approach (Hensher and Greene, 2003).[7] We find that the average WTP for a BEV is about -\$4,900. Out of current BEVs on the market as of early 2014 that have a comparable internal combustion engine (ICE) model, the BEVs are priced at an average premium of \$18,411 (see Table 5 for details). We find that the average WTP for a PHEV is nearly \$6,800. Out of PHEVs on the market as of early 2014 that have a comparable ICE model, the PHEVs are priced at an average premium of \$11,024 (see Table 5 for details). This suggests that the gap between WTP and the price premium for BEVs is very high, on the order of \$23,000, while the gap between WTP and the price premium for PHEVs is much smaller, on the order of \$4,000. State level incentives are typically a few thousand dollars, and the federal income tax incentive is up to \$7,500. This suggests that current financial incentives will stimulate fewer BEV purchases, but could stimulate more PHEV purchases. This is consistent with DeShazo, Sheldon, and Carson's (2015) finding that California's PEV rebate policy induces more marginal PHEV purchases than marginal BEV purchases.

The average survey respondent would pay approximately \$589 per year on refueling costs per \$1 increase in \$/gal equivalent. This is based on the assumption that the respondent refuels once every week and a half, and that the respondent's fuel tank capacity is 17 gallons. These are the average values based on the survey responses. Thus, the WTP for refuel savings of \$1 per gallon of \$430 implies a high discount rate, with an expected payback period of just under one year.

We find that the average respondent is willing to pay about \$900 for free single-occupant HOV lane access. Bento et al. (2014) estimate the average annual rent of a hybrid HOV sticker in southern California to be \$743, with a net present value of \$4,800. Shewmake and Jarvis (2014) estimate an average premium of \$3,200 for a hybrid with an HOV sticker,

[7]To calculate the mean WTP for each attribute, we took the mean of 10,000 random draws from the distribution of the attribute's coefficient divided by the exponential of a random draw from the distribution of the price coefficient.

which translates into a yearly value of \$625.

The mixed logit results show that there is considerable heterogeneity in preferences across BEVs and PHEVs, as well as across consumers. Sections 4.2 and 4.3 attempt to better understand the underlying sources of this heterogeneity.

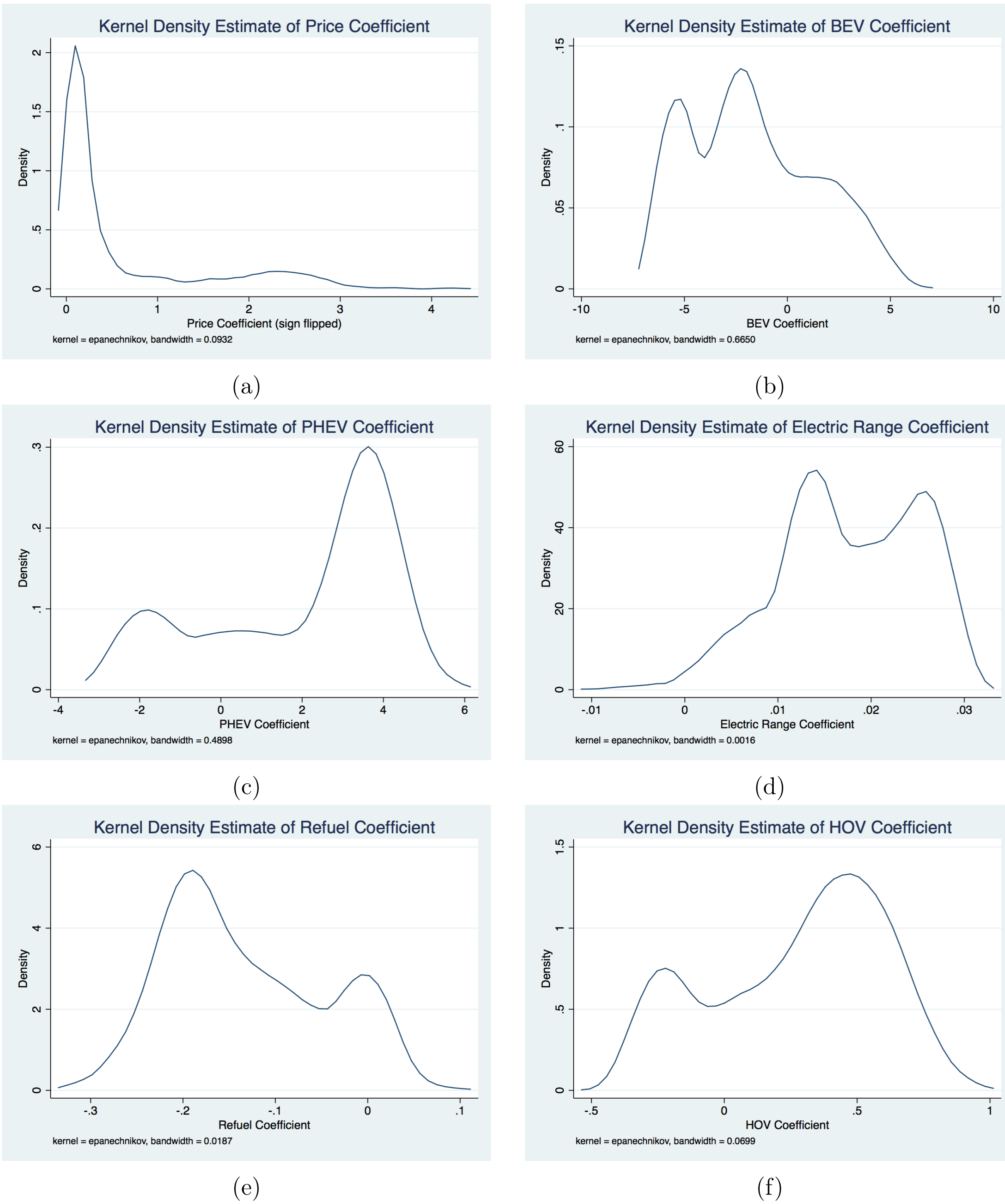
Table 3: Mixed Logit Results

	Price Normally Distributed		Price Log Normally Distributed	
	Mean	Standard Deviation	Mean	Standard Deviation
Price (\$1,000)	-0.226***	0.194**	-2.520***	0.397
	(0.028)	(0.089)	(0.257)	(0.320)
BEV	-1.301**	4.007***	-1.605***	4.348***
	(0.656)	(0.950)	(0.460)	(0.817)
PHEV	1.738**	2.745***	1.921***	2.423***
	(0.772)	(0.461)	(0.407)	(0.428)
Range	0.014***	0.004	0.017***	0.007***
	(0.002)	(0.003)	(0.002)	(0.002)
Refuel	-0.158**	0.057	-0.128	0.005
	(0.072)	(1.095)	(0.096)	(0.240)
HOV	0.311**	0.302	0.261***	0.400**
	(0.128)	(0.753)	(0.087)	(0.159)
Observations	24,940		24,940	
Log Pseudolikelihood	-5,959		-5,931	

Weighted to represent population of California new car buyers
Robust standard errors in parentheses, clustered by respondent
*** p<0.01, ** p<0.05, * p<0.1

4.2 Alternative-Specific Constant Logit Model

Tables 6 and 7 show the results of the ASC logit estimation. The coefficient on price in Table 6, -.06, is smaller in absolute value than the -2.5 estimated by the preferred specification in Table 3. The former estimate assumes the coefficient is fixed, while the latter estimate assumes the coefficient follows a log normal distribution and allows for the mean to be greater than the median, which might be the case due to a small fraction of respondents



(a) (b) (c) (d) (e) (f)

Figure 7: Mixed Logit Coefficient Distributions

Table 4: Willingness to Pay

	WTP (Price Normally Distributed)	WTP (Price Log Normally Distributed)
BEV	-$18,693	-$4,906
PHEV	$12,873	$6,783
Additional Mile of Electric Range	$81	$57
Additional $ per Gal Refuel Cost	-$874	-$430
HOV Access	$1,555	$903

Table 5: Price Comparison of Internal Combustion Engine (ICE) vehicles and PEVs of the Same Model

	ICE MSRP	BEV MSRP	Premium
Smart for Two	$13,270	$25,000	$11,730
Chevrolet Spark	$12,170	$26,685	$14,515
Ford Focus	$16,810	$35,170	$18,360
Toyota RAV4	$23,550	$49,800	$26,250
Honda Fit	$15,425	$36,625	$21,200
Avg Premium			$18,411
	ICE MSRP	PHEV MSRP	Premium
Ford C-Max	$25,170	$32,920	$7,750
Ford Fusion	$21,970	$34,700	$12,730
Honda Accord	$21,955	$39,780	$17,825
Toyota Prius Plug-In	$24,200	$29,990	$5,790
Avg Premium			$11,024

MSRPs are taken from auto makers' websites and www.edmunds.com. MSRPs as of March 2014.

being very price sensitive. The coefficients on refueling costs and HOV access are similar between Tables 3 and 6. The BEV and PHEV coefficients are not directly comparable, as those in Table 6 must be adjusted by respondent characteristics as shown in Table 7. For example, the coefficient on Gas Price in Table 7 is approximately 1.5, and the gas price in most Census Tracts during December of 2013 was greater than \$3, such that at least $3 * 1.5 = 4.5$ must be added to both the BEV and PHEV coefficients in Table 6.

Table 6: Alternative-Specific Constant Logit, Main Results

Price (\$1,000s)	-0.062***
	(0.009)
BEV	-9.701****
	(3.604)
PHEV	-8.936***
	(2.701)
Range	0.033***
	(0.003)
Range^2	-0.0001***
	(.00001)
Refuel	-0.086**
	(0.045)
HOV	0.239***
	(0.057)
Observations	24,620
Log Pseudolikelihood	-6,732

Weighted to represent population of California new car buyers
Robust standard errors in parentheses, clustered by respondent
*** p<0.01, ** p<0.05, * p<0.1

Due to the complexity of the model, we are unable to achieve convergence in the maximum likelihood estimation of the mixed logit when we include a quadratic range term in the specification. We are able to achieve convergence in the ASC logit estimation when a quadratic range term is included. When we include this term, we get more precision on the refueling cost coefficient and we find that consumers' utility for range exhibits decreasing returns. This is consistent with the literature (Bunch et al., 1993; Brownstone, Bunch, and Train, 2000). The linear and quadratic range coefficients suggest an optimal electric range

Table 7: Alternative-Specific Constant Logit, ASC Results

	BEV	PHEV
Small Body	-0.126	-0.014
	(0.210)	(0.196)
Household Vehicles	0.091	0.196*
	(0.122)	(0.112)
Outlet	0.367	0.394*
	(0.237)	(0.214)
Parking at Work	1.967***	0.809
	(0.627)	(0.566)
Commute under 20mi	-0.803**	-0.681***
	(0.316)	(0.263)
Use Gas Mode Daily	-1.302***	-1.345***
	(0.364)	(0.283)
HOV Access	0.123	0.456***
	(0.161)	(0.135)
Pro Environment	0.886***	0.427**
	(0.215)	(0.195)
Early Adopter	0.207***	0.130***
	(0.055)	(0.050)
Charging Station Density	0.004	0.010
	(0.020)	(0.020)
Gas Price	1.598	1.795**
	(0.979)	(0.714)
Low Income (<$30k)	-0.228	0.148
	(0.354)	(0.315)
High Income (>$100k)	-0.415*	-0.070
	(0.233)	(0.206)
Observations	24,620	24,620
Log Pseudolikelihood	-6,732	-6,732

Weighted to represent population of California new car buyers
Robust standard errors in parentheses, clustered by respondent
*** p<0.01, ** p<0.05, * p<0.1

of 165 miles.

Table 6 shows that all else being equal, consumers prefer PHEVs to BEVs. Table 7 shows that having pro environment preferences and self-identifying as an early adopter increase a respondent's WTP for both BEVs and PHEVs, although relatively more for BEVs.

Respondents with round-trip commutes under 20 miles are less likely to select PEVs. This may be because a shorter commute would accrue less refueling cost savings, making it more difficult for the consumer to justify the higher upfront cost of a PEV.

The environmental benefits associated with driving a PHEV depend on the relative number of miles driven in electric versus gasoline mode. While the California Air Resources Board currently assigns higher rebates to BEVs in the belief they are associated with greater environmental benefits than PHEVs, it is sometimes argued that PHEVs may result in close to the same environmental benefits if daily commuting can be done in all-electric mode (California Environmental Protection Agency, 2007). PHEVs do not invoke range anxiety or impair the ability to take longer occasional trips. The results in Table 7 support this assertion. Respondents who anticipate needing to utilize gasoline mode on a daily basis if they owned a PHEV are much less likely to purchase either a BEV or a PHEV. This effect is similar for BEVs and PHEVs, suggesting prospective PHEV drivers are equally as motivated to commute primarily in all-electric mode, even though they do not face the same total range constraints as BEVs.

The positive coefficients on outlet access in Table 7 suggest that respondents who have an electrical outlet near their home parking spot are more likely to purchase a PEV. This is consistent with earlier studies (Axsen and Kurani, 2009; Hidrue et al., 2011). Notably, outlet access appears just as important for PHEVs as BEVs, even though PHEVs do not require the electric battery be charged in order to drive the vehicle in gasoline mode. However, when we replace the outlet variable with an indicator variable for whether the respondent lives in a single-family house, this coefficient is positive and statistically significant at the 10%

level for BEVs but smaller and not statistically different from zero for PHEVs.[8] This may suggest that BEV owners are more comfortable plugging into an outlet at their single family residence while PHEV owners living in multifamily housing are also comfortable plugging into a less private or less exclusive outlet near their residential parking spot.

The coefficient on the indicator for whether a respondent parks in a garage while at work is positive and highly statistically significant for BEVs but smaller and not significant for PHEVs. Respondents with access to a parking garage at work may anticipate a higher likelihood of charging access while at work, which would increase their utility for PEVs. These coefficients suggest that workplace charging is a more important issue for BEV adoption than PHEV adoption. The coefficients on public charging station density are positive but not statistically different from zero.

The coefficients on HOV lane access are positive, but that for BEVs is smaller than that for PHEVs and not statistically significant. This suggests that new car buyers who live near HOV lanes are more likely to purchase PHEVs, and that government policies allowing free single-occupant HOV lane access increase consumer probability of purchasing PHEVs. Sheldon and DeShazo (2015) find that California's HOV lane policy had a positive impact on both BEV and PHEV adoption, with relatively more impact on the PHEV market.

The coefficient on number of household vehicles is positive for both vehicle types, although only statistically significantly greater than zero for PHEVs. This lends support to the "Hybrid Household" hypothesis that households with larger vehicle fleets are more likely to diversify their vehicle holdings with alternative vehicles (Kurani, Turrentine, and Sperling, 1996).

The coefficients on small body type are not statistically different from zero, implying that respondents who are likely to purchase a new vehicle that is a hatchback or small sedan are neither more nor less likely than other respondents to select a PEV. Although the majority of PEVs on the market have historically been smaller vehicles, this result is unsurprising

[8]If we substitute the Outlet variable with Single House, the BEV coefficient on Single House is 0.427* (0.234) and the PHEV coefficient on Single House is 0.151 (0.207), with other coefficients not significantly different. We do not include Outlet and Single House in the same specification due to concerns about collinearity.

because in our choice experiment, respondents were allowed to choose PEV versions of any body type.

4.3 Latent Class Model

Tables 8 and 9 show the results of a latent class estimation assuming three segments, using a variety of sociodemographic variables and attitudes to determine segment membership. Note that the latent class groups are helpful in explaining the kernel density estimate of coefficients. For example, Figure 7b shows that there are three peaks in the BEV coefficient distribution: one at a large negative number, the biggest at a small negative number, and the third and smallest peak at a near-zero positive number. These three peaks are consistent with the three BEV preferences of the different segments.

Table 8: Latent Class Model: Segment Preferences

	Segment 1	Segment 2	Segment 3
Price ($1,000s)	-0.193***	-0.387***	-0.024***
	(0.016)	(0.052)	(0.007)
BEV	-3.752***	-3.031***	-0.197
	(0.382)	(0.485)	(0.300)
PHEV	0.643**	-1.531***	0.511**
	(0.298)	(0.403)	(0.251)
Range	0.051***	0.013**	0.018***
	(0.003)	(0.006)	(0.003)
Range^2	-0.0002***	-.00003	-.00003***
	(0.00002)	(0.00002)	(0.00001)
Refuel	-0.219***	-0.088	-0.123**
	(0.073)	(0.105)	(0.052)
HOV	0.382***	-0.073	0.232***
	(0.089)	(0.156)	(0.064)
Class Share	42.4%	26.1%	31.5%
Observations	24,940	24,940	24,940

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8 shows consumer Segment 3 has a positive WTP for PHEVs and a WTP for BEVs that is approximately zero. This class is by far the most receptive to BEVs. Table 9 shows that self-identified environmentalists and early adopters are more likely to be in Segment 3. Consumers who reside in single-family houses and younger consumers are also more likely to be in Segment 3. These findings support the notion that demand for BEVs is driven by strong environmental preferences and eagerness to adopt new technologies. These findings also confirm earlier results that households with home charging infrastructure are relatively more likely to purchase PEVs.

Table 8 shows consumer Segment 2 has a negative WTP for both BEVs and PHEVs. This is also the most price sensitive segment. Segment 2 has less strong preferences for range and is indifferent towards refueling cost and HOV lane access, perhaps as a result of their low likelihood of selecting a PEV. The results in Table 9 show that consumers who are less educated, more conservative, less concerned about the environment, and tend not to be early adopters are more likely to belong to this segment.

Consumer Segments 2 and 3 are consistent with prevalent beliefs about the PEV market, in which there is a class of consumers that is enthusiastic about PEVs and another class that will have nothing to do with PEVs. Consumer Segment 1 is the most interesting, because this segment has more nuanced preferences and also represents the largest of the three segments. Table 8 shows consumer Segment 1 has a negative WTP for BEVs but a positive WTP for PHEVs. They are more price sensitive than Segment 3.

Consumers who have HOV lane access, who do not live in single-family houses, and who are more liberal are more likely to belong to Segment 1, as shown in Table 9. Respondents fitting this profile tend to live in urban areas. Additionally, consumers who are older, have higher incomes, and are more educated are more likely to belong to Segment 1. This segment's positive preference for PHEVs appears to stem not from environmental or early adopter preferences but rather from more pragmatic reasons such as refueling cost savings and HOV lane access. This segment's negative preference for BEVs may be in part driven

Table 9: Latent Class Model: Segment Membership

	Segment 1	Segment 2	Segment 3[†]
Household Size	-0.049	-0.238***	0.000
	(0.070)	(0.077)	
Household Vehicles	0.231**	0.172	0.000
	(0.106)	(0.113)	
Age under 35	-0.648***	-0.305	0.000
	(0.205)	(0.217)	
Age over 60	0.548**	0.504*	0.000
	(0.255)	(0.258)	
Low Income (<$30k)	0.322	0.108	0.000
	(0.262)	(0.267)	
High Income (>$100k)	0.349*	0.074	0.000
	(0.211)	(0.225)	
College Education	0.056	-0.290	0.000
	(0.187)	(0.197)	
Use Gas Mode Daily	0.005	0.793**	0.000
	(0.382)	(0.357)	
Single House	-0.398**	-0.313	0.000
	(0.194)	(0.204)	
HOV Access	0.050	-0.436***	0.000
	(0.121)	(0.133)	
Pro Environment	-0.641***	-1.088***	0.000
	(0.175)	(0.191)	
Early Adopter	-0.077*	-0.219***	0.000
	(0.046)	(0.049)	
Liberal	0.332*	-0.017	0.000
	(0.189)	(0.212)	
Constant	0.277	1.439***	0.000
	(0.405)	(0.407)	
Class Share	42.4%	26.1%	31.5%
Observations	24,940	24,940	24,940

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[†]Segment 3 is the baseline segment that the other segments are compared to.

by less access to home charging.

The latent class results show that the BEV market may be constrained since less than a third of the new car buying population seems willing to consider purchasing a BEV, all else being equal. A much larger fraction of the population, and one that breaks out of the early adopter/environmentalist niche, seems willing to consider purchasing a PHEV.

5 Implications for Policy and the Emerging Market

Results from the mixed logit model suggest that the gap between WTP and the price premium for BEVs is very high, on the order of $23,000, while the gap between WTP and the price premium for PHEVs is much smaller, on the order of $4,000. This suggests that financial incentives of a few thousand dollars, similar to current subsidy levels, will stimulate fewer BEV purchases, but could stimulate more PHEV purchases.

In the ASC logit model we find that consumers' utility for range exhibits decreasing returns. The linear and quadratic range coefficients suggest an optimal electric range of 165 miles. A similar calculation for the latent class model suggests optimal ranges for Segment 1, 2 and 3 of 127.5, 216.7, and 300 miles, respectively. Segment 3 is the most likely to choose a BEV and is the least price sensitive, so it makes sense this segment is willing to pay for a longer range. Segment 1 is more likely to purchase a PHEV, such that a more cost-effective, shorter range vehicle may be sufficient. In the ASC logit model we also find evidence that prospective PHEV drivers are equally as motivated to commute primarily in all-electric mode, even though they do not face the same total range constraints as BEVs.

In the mixed logit model, we find that the average respondent is willing to pay about $900 for free single-occupant HOV lane access. In the ASC logit model, the coefficients on HOV lane access are positive, but that for BEVs is smaller than that for PHEVs and not statistically significant. This suggests that new car buyers who live near HOV lanes are more likely to purchase PHEVs, and that government policies allowing free single-occupant HOV lane access increases consumer probability of purchasing PHEVs.

In the ASC logit model we find that charging close to home access appears just as important for PHEVs as BEVs, even though PHEVs do not require the electric battery to be charged in order to drive the vehicle in gasoline mode. These results suggest that home charging is just as important to consumers considering a PHEV purchase. However, we also find evidence that BEV owners are more comfortable plugging into an outlet at their single family residence while PHEV owners living in multifamily housing are also comfortable plugging into a less private or less exclusive outlet near their residential parking spot. Our latent class model similarly suggests that consumers living in a single-family household are more likely to purchase BEVs. In the ASC logit model we also find evidence that the ability to charge at work is more important for BEV adoption than PHEV adoption.

The latent class model reveals three distinct consumer segments. About a quarter of the new car buyer population seems to be less urban, more conservative, and have strong negative preferences for all PEVs. A third of the population has pro-environmental preferences and a tendency for early adoption. This is the only segment that does not have a strong negative preference for BEVs. The last segment, Segment 1, tends to be more urban, older, higher income, and more educated. These consumers have a strong negative preference for BEVs but a strong positive preference for PHEVs. This positive preference for PHEVs appears not to stem from environmental or early adopter preferences. This segment's negative preference for BEVs may be in part driven by less access to home charging.

The latent class results show that the BEV market may be constrained since less than a third of the new car buying population seems willing to consider purchasing a BEV, all else being equal. On the other hand, a much larger and more general population seems willing to consider purchasing a PHEV and even has a positive willingness to pay for this technology relative to a conventional gasoline vehicle. This suggests that the addition of PHEVs to the market may stimulate PEV demand in consumer segments who would otherwise be unlikely to purchase a BEV. These findings also imply that many PHEV purchasers would not purchase a BEV, and such sales would represent growth in the overall PEV market rather than cannibalization of the BEV market. We speculate that due to the strong negative preferences for BEVs in most of the population and cost differentials that are large relative to subsidy levels being considered by policy makers, much of the future growth of the PEV market will be driven by demand for PHEVs from Segment 1.

References

Achtnicht, Martin, Georg Bühler, and Claudia Hermeling (2012), "The impact of fuel availability on demand for alternative-fuel vehicles," *Transportation Research Part D*, 17: 262-269.

Axsen, Jonn, and Kenneth S. Kurani (2009), "Early US market for plug-in hybrid electric vehicles," Transportation Research Record: *Journal of the Transportation Research Board* 2139, no. 1: 64-72.

Axsen, John and Kenneth S. Kurani (2013), "Hybrid, plug-in hybrid, or electric-What do car buyers want?," *Energy Policy*, 61: 532-543.

Bento, Antonio, Daniel Kaffine, Kevin Roth, and Matthew Zaragoza-Watkins (2014), "The effects of regulation in the presence of multiple unpriced externalities: Evidence from the transportation sector," *American Economic Journal: Economic Policy*, 6(3): 1-29.

Brownstone, David, David S. Bunch, and Kenneth Train (2000), "Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles," *Transportation Research Part B*, 34: 315-338.

Bunch, David S., Mark Bradley, Thomas F. Golob, Ryuichi Kitamura, and Gareth P. Occhiuzzo (1993), "Demand for clean-fuel vehicles in California: A discrete-choice stated preference pilot project," *Transportation Research Part A*, 27A(3): 237-253.

California Environmental Protection Agency (2007), Status report on the California Air Resources Board's Zero Emission Vehicle Program.

Caperello, Nicolette D. and Kenneth S. Kurani (2012), "Households' stories of their encounters with a plug-in hybrid electric vehicle," *Environment and Behavior*, 44(4): 493-508.

DeShazo, J.R., Tamara L. Sheldon and Richard T. Carson (2015), "Designing policy incentives for cleaner technologies: Lessons from California's plug-in electric vehicle rebate program," *Working Paper*, Luskin School of Public Affairs, University of California, Los Angeles.

Ewing, Gordon and Emine Sarigöllü (2000), "Assessing consumer preferences for clean-fuel vehicles: A discrete choice experiment," *Journal of Public Policy and Marketing*, 19(1): 106-118.

Egbue, Ona, and Suzanna Long (2012), "Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions," *Energy Policy*, 48: 717-729.

Golob, Thomas F., Ryuichi Kitamura, Mark Bradley, and David S. Bunch (1993), "Predicting the market penetration of electric and clean-fuel vehicles," *The Science of the Total Environment*, 134: 371-381.

Graham-Rowe, Ella, Benjamin Gardner, Charles Abraham, Stephen Skippon, Helga Dittmar, Rebecca Hutchins, and Jenny Stannard (2012), "Mainstream consumers driving plug-in battery-electric and plug-in hybrid electric cars: A qualitative analysis of responses and evaluations," *Transportation Research Part A*, 46: 140-153.

Hensher, David A. and William H. Greene (2003), "The Mixed Logit model: The state of practice," *Transportation*, 30:133-176.

Hidrue, Michael K., George R. Parsons, Willett Kempton, and Meryl P. Gardner (2011), "Willingness to pay for electric vehicles and their attributes," *Resource and Energy Economics*, 33: 686-705.

Khan, Mobashwir, and Kara M. Kockelman (2012), "Predicting the market potential of plug-in electric vehicles using multiday GPS data," *Energy Policy*, 46: 225-233.

Kurani, Kenneth S., Reid R. Heffner, and Tom Turrentine (2008),"Driving plug-in hybrid electric vehicles: Reports from US drivers of HEVs converted to PHEVs, circa 2006-07," Institute of Transportation Studies.

Kurani, Kenneth S., Thomas Turrentine, and Daniel Sperling (1996), "Testing electric vehicle demand in 'hybrid households' using a reflexive survey," *Transportation Research Part D*, 1(2): 131-150.

McFadden, Daniel (1974), "Conditional logit analysis of qualitative choice behaviour," in *Frontiers in Econometrics*, edited by P. Zarembka (New York: Academic Press), pages 105-142.

Qian, Lixian and Didier Soopramanien (2011), "Heterogeneous consumer preferences for alternative fuel cars in China," *Transportation Research Part D*, 16: 607-613.

Revelt, David, and Kenneth Train (2000), "Customer-specific taste parameters and mixed logit: Households' choice of electricity supplier," *Working Paper*, Department of Economics, University of California, Berkeley.

Scarpa, Riccardo, and John M. Rose (2008), "Design efficiency for non-market valuation with choice modelling: how to measure it, what to report and why," *Australian Journal of Agricultural and Resource Economics*, 52(3): 253-282.

Sheldon, Tamara L., and J.R. DeShazo (2015), "How does the presence of HOV lanes affect plug-in electric vehicle adoption in California? A generalized propensity score approach," *Working Paper*, Department of Economics, University of South Carolina.

Shewmake, Sharon, and Lovell Jarvis (2014), "Hybrid cars and HOV lanes," *Transportation Research Part A*, 67: 304-319.

Train, Kenneth E. (1998), "Recreation demand models with taste differences over people, *Land Economics*, 74(2): 230-239.

A Appendix

Table A.1: Definition of Variables

Variable Name	Description
BEV	Indicator for whether the chosen vehicle is a BEV
PHEV	Indicator for whether the chosen vehicle is a PHEV
Range	Electric range of chosen vehicle (miles)
Refuel	Refueling cost of chosen vehicle ($ per gallon equivalent)
HOV	Indicator for whether the chosen vehicle is granted free single-occupant access to high occupancy vehicle lanes
Small Body	Binary variable for if the respondent indicated that the vehicle she is most likely to select for her next new vehicle purchase is a compact car, midsize car, or hatchback
Household Size	Number of members of household, including respondent
Household Vehicles	Number of vehicles in respondent's household
Age under 35	Binary variable for if respondent is less than 35 years old
Age over 60	Binary variable for if respondent is more than 60 years old
Outlet	Binary variable that equals 1 if the respondent indicated an electrical outlet located within 100 feet of her home parking spot
Single House	Binary variable for if respondent lives in a one-family house detached from any other house or a one-family house or condo attached to one or more houses
Parking at Work	Binary variable for if the respondent indicated she parks her vehicle in a commercial lot or garage while at work
Commute under 20mi	Binary variable for if the respondent indicated that the shortest electric range she would need for daily commute is under 20 miles
Use Gas Mode Daily	Binary variable for if the respondent purchased a PHEV, she anticipates using gasoline mode almost daily

Continued on next page

Table A.1 – continued from previous page

Variable Name	Description
HOV Access	Binary variable that equals 1 if the respondent indicated she could use HOV lanes for her daily commute or weekend travel
Pro Environment	Binary variable for if the respondent indicates that environmental issues are very or extremely important to her personally
Early Adopter	Early adopter score[1]
Liberal	Binary variable for if the respondent identifies her political ideology as liberal (versus conservative or moderate)
Charging Station Density	Publicly available level 2 charging stations within a 5 mile radius of population centroid of the Census Tract in which the respondent (in tens) lives as of December 2013
Gas Price	Average price per gallon of gasoline of the Census Tract in which the respondent lives in December 2013
High Income (>$100k)	Binary variable that equals 1 if the respondent's household income is greater than $100,000
Low Income (<$30k)	Binary variable that equals 1 if the respondent's household income is less than $30,000
College Education	Binary variable for if respondent has a Bachelor's degree or higher education

[1]Early adopter score is between 0 and 5. For each of the five following statements, one point is allocated towards the early adopter score if the respondent agrees or strongly agrees with the statement: (1) I usually try new products before other people do, (2) I often try new brands because I like variety and get bored with the same, (3) When I shop I look for what is new, (4) I like to be the first among my family and friends to try something new, and (5) I like to tell others about new brands or technology