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Willingness to pay for electric vehicles and their attributes☆

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ABSTRACT

This article presents a stated preference study of electric vehicle choice using data from a national survey. We used a choice experiment wherein 3029 respondents were asked to choose between their preferred gasoline vehicle and two electric versions of that preferred vehicle. We estimated a latent class random utility model and used the results to estimate the willingness to pay for five electric vehicle attributes: driving range, charging time, fuel cost saving, pollution reduction, and performance. Driving range, fuel cost savings, and charging time led in importance to respondents. Individuals were willing to pay (wtp) from \$35 to \$75 for a mile of added driving range, with incremental wtp per mile decreasing at higher distances. They were willing to pay from \$425 to \$3250 per hour reduction in charging time (for a 50 mile charge). Respondents capitalized about 5 years of fuel saving into the purchase price of an electric vehicle. We simulated our model over a range of electric vehicle configurations and found that people with the highest values for electric vehicles were willing to pay a premium above their wtp for a gasoline vehicle that ranged from \$6000 to \$16,000 for electric vehicles with the most desirable attributes. At the same time, our results suggest that battery cost must drop significantly before electric vehicles will find a mass market without subsidy.

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1. Introduction

Concerns about climate change and energy security, along with advances in battery technology, have stimulated a renewed interest in electric vehicles. The Obama administration has set a goal of one million plug-in vehicles on the road by 2015 and has introduced laws and policies supporting this goal. These include a multi-billion dollar investment in automotive battery manufacturing, tax credits and loans for plug-in vehicle manufacturing and purchase, and research initiatives. Some states have adopted their own initiatives as well. Encouraged by these actions, along with advances in lithium-ion battery technology and recent success stories for hybrid electric vehicles, automakers have begun a major push to develop plug-in battery vehicles. Indeed, all major automakers have R&D programs for electric vehicles (EVs) and have indicated their intentions to begin mass production within the next few years.[1]

We are interested in the potential consumer demand for electric vehicles and whether or not they might become economic. To this end, we used a stated choice experiment to estimate how much consumers are willing to pay for EVs with different design features. We focused on pure electric vehicles rather than plug-in hybrid electric vehicles. Economic analyses of EVs to date have not been favorable, largely due to high battery cost, short driving range, long charging times, and limited recharging infrastructure. However, recent advances in technology suggest that driving range can be extended, charging time shortened, and battery cost lowered. Also, after a few years of mass production, the unit cost for EVs, like most new technologies, is likely to fall. The time seems right for another look at the economic potential for EVs. The latest round of published studies, which we discuss shortly, were completed around the year 2000.

We carried out a nationwide survey of potential car buyers in 2009 using a web-based instrument. We offered respondents hypothetical electric versions of their preferred gasoline vehicle at varying prices and with varying attributes (e.g., driving range and charging time). Then, using a latent class random utility model we estimated the demand for EVs. We estimated a model with two latent classes, labeled here as EV-oriented and GV-oriented drivers, where GV is for gasoline vehicle. Using parameter estimates from our model we then estimated respondents' willingness to pay to switch from their preferred GV to several hypothetical EVs. In a final section of this paper, we compare the willingness to pay estimates with the estimated incremental cost of an EV over a GV based on battery cost projections.

Most demand studies for EVs to date, like ours, have used stated preference analysis in some form. The earliest studies started in response to the 1970s oil crisis. Beggs et al. (1981) and Calfee (1985) are probably the best known. Both targeted multicar households with driving and demographic characteristics likely to favor EVs. Both found low market share for EVs and "range anxiety" as the primary concern for consumers. Both also found significant preference heterogeneity.

Another wave of studies started in the early 1990s in response to California's zero-emission vehicle mandate. These studies tried to predict the potential demand for EVs in California. Major among these were Bunch et al. (1993), Brownstone et al. (1996, 2000), and Brownstone and Train (1999). There were also some similar studies outside California including Tompkins et al. (1998), Ewing and Sarigollu (2000), and Dagsvike et al. (2002). These studies differ from the earlier ones in at least four ways. First, they moved from targeting multicar households to targeting the entire population. Second, they included a measure of emission level as a standard vehicle attribute. Third, the choice set typically included other vehicle technologies such as concentrated natural gas, hybrid electric, methanol, and ethanol as alternatives for conventional gasoline vehicles. Finally, they employed some form of survey customization (different respondents receiving different choice options) to increase the relevance of the choice task. A common finding in these studies was that EVs have low likelihood of penetrating the market. Limited driving range, long charging time, and high purchase price were identified as the main concerns for consumers. They also found that people were willing to pay a significant amount to reduce emission and save on gas (see Bunch et al., 1993; Tompkins et al., 1998; Ewing and Sarigollu, 2000). Table 1 summarizes these past EV studies.

[1] Interest in electric vehicles is not new. In 1900 nearly 40% of all cars were electric, Thomas Edison experimented with electric vehicles, and there was a notable surge in interest during the oil crisis in the 1970s. For an interesting historical account of electric vehicles see Anderson and Anderson (2005).

Table 1
Summary of past EV studies.

Study	Econometric model	Number of choice sets, attributes, and levels	List of attributes used
Beggs et al. (1981)	Ranked logit	16, 8, NA	Price, fuel cost, range, top speed, number of seats, warranty, acceleration, air conditioning
Calfee (1985)	Disaggregate MNL	30, 5, NA	Price, operating cost, range, top speed, number of seats
Bunch et al. (1993)	MNL and Nested logit	5, 7, 4	Price, fuel cost, range, acceleration, fuel availability, emission reduction, dedicated versus multi-fuel capability
Brownstone and Train (1999); Brownstone et al. (2000)	MNL and Mixed logit; Joint SP/RP Mixed logit	2, 13, 4	The two papers used the same data/study. Hence the list in the attribute column and the number of choice sets, attributes and levels column are the same for both. Price, range, home refueling time, home refueling cost, service station refueling time, service station refueling cost, service station availability, acceleration, top speed, tailpipe emission, vehicle size, body type, luggage space
Ewing and Sarigollu (1998, 2000)	MNL	9, 7, 3	Price, fuel cost, repair and maintenance cost, commuting time, acceleration, range, charging time
Dagsvike et al. (2002)	Ranked logit	15, 4, NA	Price, fuel cost, range, top speed

NA, not available.

Our analysis builds on this body of work and contributes to the literature by using more recent data, using a method that focuses respondents on EV attributes (we offer respondents ''EV-equivalents'' of their preferred GV to control for extraneous features), estimating a latent class model, and comparing willingness to pay (wtp) to incremental EV cost based on battery cost projections.

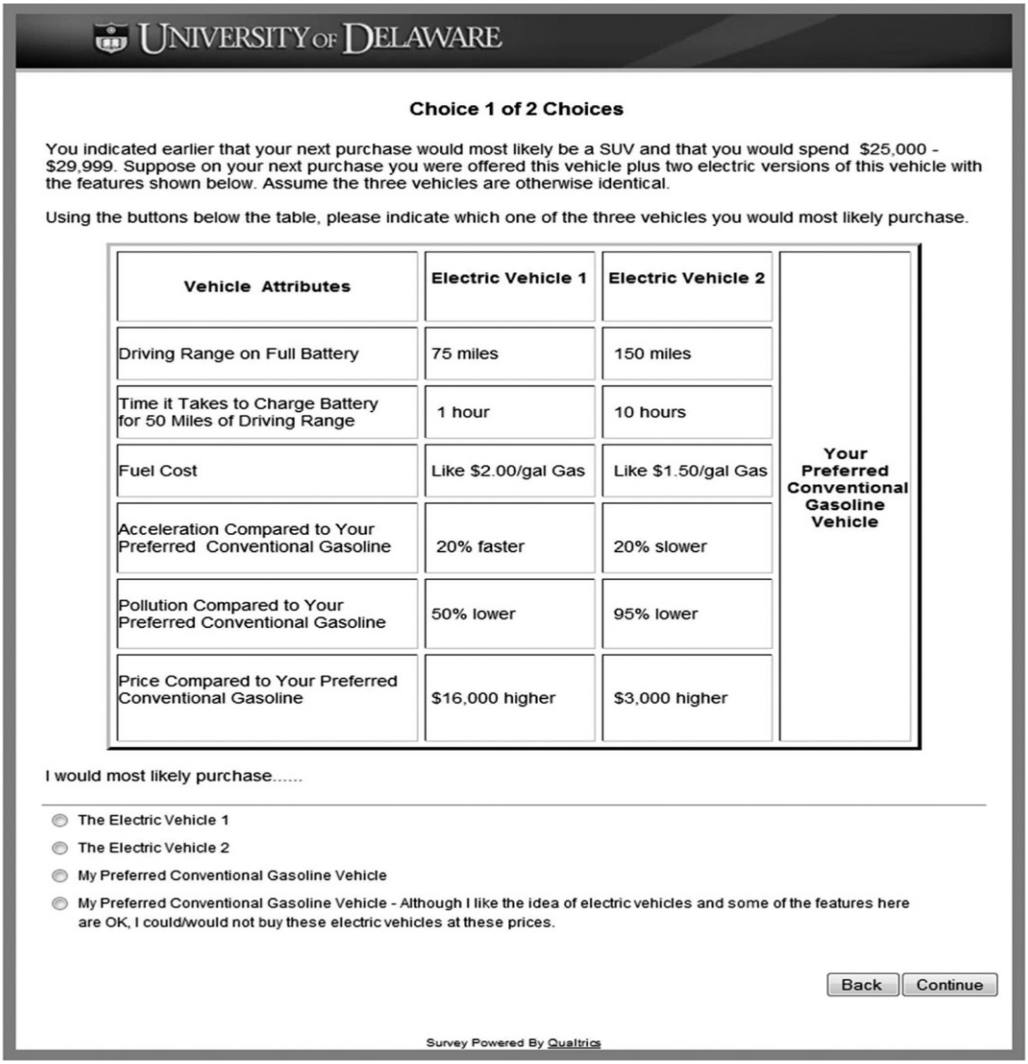
2. Survey, sampling, and study design

We used an internet-based survey developed between September 2008 and October 2009. During this period we designed and pretested the survey and made multiple improvements and adjustments based on three focus groups, three pilot pretests, and suggestions from presentations of our study design at two academic workshops.[2]

The final version of the survey had four parts: (i) background questions on car ownership and driving habits, (ii) description of conventional EVs followed by two choice questions, (iii) description of vehicle-to-grid EVs followed by two more choice questions, and (iv) a series of attitudinal and demographic questions. The survey included a brief ''cheap talk'' script, intended to encourage realistic responses.[3] It also included debriefing questions to get respondents' feedback regarding the relevance of each attribute in their choice and to ascertain the clarity and neutrality of the information provided on the survey. The survey wording and questions were probably also improved due to some coauthors' work with our EV policy and technology group that has been driving EVs and explaining EV

[2] Paper presentation at the Academy of Marketing Sciences Annual Workshop: Marketing for a Better World, May 20–23, 2009; and poster presentation at the Association of Environmental and Resource Economists Workshop: Energy and the Environment, June 18–20, 2009.

[3] The following script proceeded our choice questions: ''Please treat each choice as though it were an actual purchase with real dollars on the line''.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Choice 1 of 2 Choices

You indicated earlier that your next purchase would most likely be a SUV and that you would spend $25,000 - $29,999. Suppose on your next purchase you were offered this vehicle plus two electric versions of this vehicle with the features shown below. Assume the three vehicles are otherwise identical.

Using the buttons below the table, please indicate which one of the three vehicles you would most likely purchase.

Vehicle Attributes	Electric Vehicle 1	Electric Vehicle 2	
Driving Range on Full Battery	75 miles	150 miles	Your Preferred Conventional Gasoline Vehicle
Time it Takes to Charge Battery for 50 Miles of Driving Range	1 hour	10 hours	
Fuel Cost	Like $2.00/gal Gas	Like $1.50/gal Gas	
Acceleration Compared to Your Preferred Conventional Gasoline	20% faster	20% slower	
Pollution Compared to Your Preferred Conventional Gasoline	50% lower	95% lower	
Price Compared to Your Preferred Conventional Gasoline	$16,000 higher	$3,000 higher	

I would most likely purchase......

- The Electric Vehicle 1
- The Electric Vehicle 2
- My Preferred Conventional Gasoline Vehicle
- My Preferred Conventional Gasoline Vehicle - Although I like the idea of electric vehicles and some of the features here are OK, I could/would not buy these electric vehicles at these prices.

Back Continue

Survey Powered By Qualtrics

Fig. 1. Sample EV choice set in questionairre.

characteristics at demonstrations and conferences for the prior three years. The vehicle-to-grid EV choice data from part (iii) are not analyzed in this paper.[4]

The first stage of the survey covered the respondent's current driving habits, vehicle ownership, and details on the vehicle they are most likely to purchase next. The latter included the expected size, type, price, and timing of purchase. Next was a descriptive text on the similarities and differences of EVs and GVs. Then respondents were asked two choice questions in a conjoint format. A sample question is shown in Fig. 1. In each of the two choice questions, respondents were asked to consider three vehicles: two EVs and one GV. The GV was their "preferred gasoline vehicle" and was based on

[4] Vehicle-to-Grid (V2G) electric vehicles allow owners to sell their battery capacity to electric grid operators during times the vehicle is not being driven, and thus have the potential of making EVs more economical (Kempton and Tomić, 2005). In the V2G choice questions we analyzed different V2G contract terms to establish their feasibility. These data will be analyzed in a second paper.

Table 2
Attributes and levels used in the choice experiment.

Attributes	Levels
Price relative to your preferred GV	Same $1000 higher $2000 higher $3000 higher $4000 higher $8000 higher $16,000 higher $24,000 higher
Driving range on full battery	75 miles 150 miles 200 miles 300 miles
Time it takes to charge battery for 50 miles of driving range	10 min 1 h 5 h 10 h
Acceleration relative to your preferred GV	20% slower 5% slower 5% faster 20% faster
Pollution relative to your preferred GV	95% lower 75% lower 50% lower 25% lower
Fuel cost	Like $0.50/gal gas Like $1.00/gal gas Like $1.50/gal gas Like $2.00/gal gas

the response they gave to a previous question on the type of vehicle they were most likely to purchase next (it could be gasoline or a hybrid like a Toyota Prius). The preferred GV and the amount of money the respondent planned to spend was mentioned in the preamble to the question, reminding the respondent what he or she had reported previously. Because the survey was web-based, the text of questions could include values from, or be adjusted based on, prior answers. In each three-way choice, we treated the GV as the opt-out alternative. The two EVs were described as electric versions of their preferred GV. Respondents were told that, other than the characteristics listed, the EVs were identical to their preferred GV. This allowed us, in principle, to control for all other design features of the vehicle – interior and exterior amenities, size, look, safety, reliability, and so forth. This enabled us to focus on a key set of attributes of interest without the choice question becoming too complex. The attributes and their levels are shown in Table 2.[5]

Most of the attributes are self-explanatory and capture what we expected would matter to car buyers in comparing EVs and GVs – driving range, charging time, fuel saving, pollution reduction, performance, and price difference. Price was defined as the amount the respondent would pay above the price of the respondent's preferred GV. This puts the focus on the tradeoff between the extra dollars being spent on an EV and the attributes one would receive in exchange. Charging time was defined as the time needed to charge the battery for 50 miles. The average vehicle is driven less than 40 miles/day, so this is a little more than a typical daily charging time to recharge, or enough to extend a trip 50 miles. The electric refuel cost was defined in gas-equivalent terms (e.g., "like $1.50 per gallon

[5] A drawback of this strategy is that we miss substitution across vehicle types, such as buying a new smaller EV instead of a new larger GV. People may employ this type of substitution to lower the purchase price for an EV.

Table 3
Distribution of choices among alternatives.

Alternatives	Without yea-saying correction (%) $N=1996$	With yea-saying correction (%) $N=1033$
Electric vehicle-1	23.5	23.3
Electric vehicle-2	27.1	25.0
My preferred gasoline vehicle	49.4	23.6
My preferred gasoline vehicle – although I like the idea of electric vehicles and some of the features here are ok, I could/would not buy these electric vehicles at these prices	–	28.1
Total	100	100

gas''). This pretested far better than the other measures we considered and was independent of miles driven by the respondent.[6] Pollution reduction was included as an indicator of the desire to buy more environmentally beneficial goods. Finally, acceleration was included as a proxy for performance differences between EVs and GVs.

We used SAS's choice macro function (Kuhfeld, 2005) to generate the choice sets. Given an a priori parameter vector β, the algorithm for this macro searches for a design that minimizes the variance of the estimated parameters. We used data from our last pretest to estimate the a priori parameters.[7] A total of 243 respondents participated in the pretest, each answering two choice questions. This gave us 486 observations that we used to estimate a simple multinomial logit model. The parameter estimates from this model were then used as the a priori parameters in developing the final choice design. The final design had 48 choice sets in 24 blocks and a D-efficiency of 4.8. The blocks were randomly assigned to respondents during the survey.

The response options for our choice experiment include a 'yea-say' correction shown as the last response at the bottom of Fig. 1. We were concerned that respondents might choose an electric option to register their support for the concept of EVs even though they would not actually purchase an EV at the cost and configuration offered. The yea-say option allowed people to say ''I like the idea of EVs'' (registering favor with concept) ''but not at these prices'' (showing their real likelihood of purchase). We conducted a treatment on this variable to see if it would indeed have any effect. About one-third of the sample had the yea-say correction response included. Table 3 shows the breakdown by responses to all our choice experiment questions. There is a nice distribution across the response categories suggesting that our levels were offered over reasonable ranges – about a 50–50 split between EV and GV. Also, there appears to be very little yea-saying. That is, even with the additional response option, the selection of EVs dropped by only 2%.

Our sample was selected to be representative of US residents over 17 years of age. A qualifying question asked if they intended to spend more than \$10,000 the next time they purchase a vehicle. We used the \$10,000 cut-off because we felt few people who planned to spend less than this would be in the near-term market for EVs. The number of completed surveys was 3029. The survey was administered by Survey Sampling International (SSI) and was collected so as to mimic the general population along the lines of income, age, education, and population by region.[8] The computer-based questionnaire delivery allowed us to design our survey with skip patterns and questions tailored to respondent-specific data such as car type planned for next purchase. Table 4 compares our sample to the national census. Since we had SSI mimic the census, we have nearly the same age distribution, income distribution and population size by region as the census. Our sample is also close to national

[6] We also considered defining fuel savings as cost to fully charge the battery, absolute fuel savings in dollars per year for EV versus GV, or fuel cost savings per mile driven.

[7] We used a linear design to develop the choice sets for the pretest.

[8] Because of the way SSI administers the survey, response rate calculations are not possible. SSI dispatches the survey to its panel until the agreed number of completed surveys is obtained. Since we do not know whether those who have not completed the survey at the time it was terminated are non-responders or late responders, calculating response rate is not meaningful.

Table 4
Comparing sample and census data.

Variable	Sample (%)	Census (%)
Male	43.0	48.7
Age distribution		
18–24	12.0	12.9
25–44	39.4	36.3
45–64	34.7	33.9
65–84	13.8	14.4
85 or above	0.17	2.5
Educational achievement		
High school incomplete	2.0	15.7
High school complete	39.2	30.0
Some college	21.7	29.3
BA or higher	36.7	25.0
Household income distribution		
Less than 10,000	4	7.2
$10,000–$14,999	3.3	5.5
$15,000–$24,999	10.2	10.6
$25,000–$34,999	13	10.6
$35,000–$49,999	19.1	14.2
$50,000–$74,999	22.5	18.8
$75,000–$99,999	13.5	12.5
$100,000–$149,999	10.3	12.2
$150,000–$199,999	1.9	4.3
$200,000 or more	1.5	4.2
Type of residence		
House	72.8	69.2
Apartment/condo	20.8	24.6
Mobile or other housing type	6.4	6.2
Number of vehicles in a household		
No vehicle	4.2	8.8
1 vehicle	34	33.4
2 vehicles	40.3	37.8
3 or more vehicles	21.5	20.0

Census Data Source: U.S. Census Bureau, 2008 American Community Survey.

statistics in number of vehicles per household and type of residence, variables important to EV choice. Our sample somewhat under-represents men and less educated persons. The latter is, no doubt, due to our prescreening exclusion of respondents purchasing cars less than $10,000. Descriptive statistics for the variables used in our model are shown in Table 5.

3. A latent class random utility model

We estimated a latent class random utility model using the choice data described above (see Swait, 1994).[9] The model allows us to group respondents into different preference classes based on individual characteristics and attitudinal responses. It is easiest to discuss the model in two parts – the choice model and then the class membership model.

The random utility portion is a discrete choice model in which respondents choose one of the three vehicles offered in our choice experiment – two electric and one gasoline. See the questions shown in Fig. 1.

Using each person's preferred GV as the opt-out alternative and letting the EV depend on the vehicle characteristics in our experiment gives the following random utilities for a given person on each choice occasion

[9] We compared mixed logit and latent class models (which is actually a mixed logit variant) on the basis of estimated parameters, non-nested test statistics, and within sample prediction. The latent class model provided better fit than the mixed logit model.

Table 5
Definition and descriptive statistics (N = 3029) for variables used in LC model. Either % or mean is shown, depending on whether the variable is dichotomous or not.

Variable	Description	% in sample	Mean (SD)
Young	1 if 18–35 years of age; 0 otherwise	30	
Middle age	1 if 36–55 years of age; 0 otherwise	43	
Old	1 if 56 years of age or above; 0 otherwise	27	
Male	1 if male; 0 otherwise	43	
College	1 if completed a BA or higher degree; 0 otherwise	37	
Income	Household income (2009 $)		$60,357 ($42,398)
Car price	Expected amount spent on next vehicle		$23,365 ($9,607)
Expected gasoline price	Expected price of regular gasoline in 5 years (nominal dollars)		$4.4 ($1.7)
Multicar	1 if household owns 2 or more cars; 0 otherwise	62	
Hybrid	1 if household plans to buy a hybrid on next car purchase; 0 otherwise	33	
Outlet	1 if the respondent is very likely or somewhat likely to have a place to install an outlet (charger) at their home at the time of next vehicle purchase; 0 otherwise	77	
New goods	1 if respondent has a tendency to buy new products that come on the market; 0 otherwise	57	
Long drive	1 if respondent expects to drive more than 100miles/day at least one day a month; 0 otherwise	70	
Small car	1 if respondent plans to buy small passenger car on next purchase; 0 otherwise	17	
Medium car	1 if respondent plans to buy medium or large passenger car on next purchase; 0 otherwise	41	
Large car	1 if respondent plans to buy an SUV, pickup-truck, or Van on next purchase; 0 otherwise	42	
Major green	1 if respondent reported making major change in life style and shopping habits in the past 5 years to help the environment; 0 otherwise	23	
Minor green	1 if respondent reported making minor change in life style and shopping habits in the past 5 years to help the environment; 0 otherwise	60	
Not green	1 if respondent reported no change in life style and shopping habits in the past 5 years to help the environment; 0 otherwise	17	

$$\begin{aligned} U_i &= \beta_p \Delta p_i + \boldsymbol{\beta}_x \boldsymbol{x}_i + \varepsilon_i \\ U_0 &= \varepsilon_0 \end{aligned} \tag{1}$$

where i = 1, 2 for the two EVs and i = 0 for the GV.

The vector $\mathbf{x}_i$ includes all of the attributes used in the choice experiment: driving range, charging time, pollution reduction, performance, and fuel cost saving. Δp_i is the price difference for the EV versus the GV. Under the usual assumption of independent and identically distributed (iid) extreme value errors in (1), we have the following logit probability for vehicle choice for any given person

$$L(\boldsymbol{\beta}) = \frac{\delta_1 \exp(\beta_P \Delta p_1 + \boldsymbol{\beta}_x \boldsymbol{x}_1)}{I} + \frac{\delta_2 \exp(\beta_P \Delta p_2 + \boldsymbol{\beta}_x \boldsymbol{x}_2)}{I} + \frac{\delta_0}{I} \tag{2}$$

where δ_1 = 1 if the respondent chooses EV 1; δ_2 = 1 if the respondent chooses EV 2; δ_0 = 1 if the respondent chooses GV; $I = 1 + \sum_{i=1}^{2} \exp(\beta_P \Delta p_i + \boldsymbol{\beta}_x \boldsymbol{x}_i)$; and $\boldsymbol{\beta}$ = ($\boldsymbol{\beta}_p$, $\boldsymbol{\beta}_x$).

The latent class portion of the model allows for preference heterogeneity across the population. The model assumes there are C preference groups (classes) where the number of groups is unknown. Each group has its own set of random utilities with its own parameters $\boldsymbol{\beta}^c$ in Eq. (1). Class membership for each person is unknown. The model assumes each person has some positive probability of membership in each preference group and assigns people probabilistically to each group as a function of individual characteristics. The number of groups is determined statistically. The probability of observing a respondent select a vehicle in our latent class model is

$$S(\boldsymbol{\alpha}, \boldsymbol{\beta}) = \sum_{c=1}^{C} \frac{\exp(\boldsymbol{\alpha}^c \mathbf{z})}{\sum_{c'=1}^{C} \exp(\boldsymbol{\alpha}^{c'} \mathbf{z})} \cdot L(\boldsymbol{\beta}^c) \tag{3}$$

where $\mathbf{z}$ = vector of individual characteristics; C is the number of latent classes; $\boldsymbol{\beta} = (\boldsymbol{\beta}^1, \ldots, \boldsymbol{\beta}^c)$, $\boldsymbol{\alpha} = (\boldsymbol{\alpha}^1, \ldots, \boldsymbol{\alpha}^c)$; and one $\boldsymbol{\alpha}^c$ vector is arbitrarily set of zero for normalization.

The term $\exp(\boldsymbol{\alpha}^c \mathbf{z}) / \sum_{c'=1}^{C} \exp(\boldsymbol{\alpha}^{c'} \mathbf{z})$ is the probability of membership in class c. $L(\boldsymbol{\beta}^c)$ is the logit probability from Eq. (2), now defined for class c. There are C sets of $\boldsymbol{\beta}^c$ and C-1 sets of $\boldsymbol{\alpha}^c$. Only C-1 sets of the latent class parameters are identified. The classes are said to be 'latent' because respondents are not actually observed being the member of any given preference group. In our interpretation of the model, each person has a weighted class membership. The weights are by class and are predicted by the model. The parameters are estimated using maximum likelihood and the number of preference groups is determined using a Bayesian Information Criterion (BIC). Eq. (3) is an entry in the likelihood function for each choice by each person.

The latent class (LC) model then captures preference heterogeneity by allowing different preference orderings over the vehicles, with some classes having greater propensity for buying electric than others. Shonkwiler and Shaw (2003) and Swait (2007) show that the LC model is not constrained by the iia property of the MNL model. However, as pointed out by Greene and Hensher (2003), the LC model assumes independence of multiple choices made by the same individual.

4. Estimation results

4.1. Latent class membership

The class membership portion of our model is shown in Table 6. The definitions of the variables in Table 6 are given in Table 5. We estimated the model using 2, 3, and 4 latent classes. With four classes, the value of the estimated parameters started to deteriorate, giving large standard errors and inflated parameter estimates. This is considered an indication to stop looking for more classes (Louviere et al.,

Table 6
Class membership model (GV-oriented is the excluded class).

Variables	Coefficient	*T*-stat.	Odds ratio
Class membership constant	−2.9	−11.5	0.06
Young[a]	0.81	6.1	2.2
Middle age[a]	0.26	2.3	1.3
Male	0.10	1.0	1.1
College	0.24	2.3	1.3
Income (in 000)	−0.0018	−1.4	0.99
Expected gasoline price (in $/gall)	0.08	3.0	1.08
Hybrid	0.84	7.9	2.3
Outlet	1.18	10.3	3.3
Multicar	−0.13	−0.12	0.9
Small car[b]	0.36	2.6	1.4
Medium car[b]	0.23	2.3	1.3
Long drive	0.20	2.0	1.2
Major green[c]	1.05	6.9	2.9
Minor green[c]	0.63	4.9	1.9
New goods	0.46	4.9	1.6
Log likelihood value	−4929		
Sample size	6058		

See Table 4 for variable definitions.
[a] Excluded category is Old (>56).
[b] Excluded category is Large car.
[c] Excluded category is Not green.

2000, p. 289). We computed two information criteria (Bayesian and Akaki) for each latent class model.[10] The Bayesian criterion selects a two-class model while the Akaki criterion selects a four-class model. We decided to use the two-class model. The two preference classes had a clear interpretation: one class was more likely to select EVs and the other more likely to stay with GVs. We labeled our classes accordingly as EV-oriented and GV-oriented.

The number of preference classes identified in our study empirically confirms earlier suggestions made by Santini and Vyas (2005). Building on the intuition of diffusion models, Santini and Vyas (2005) suggested using two sets of coefficients for predicting the adoption of alternative fuel vehicles. What they refer to as an early group (a group that includes early adopters and early buyers), corresponds to our EV class. However, as can be seen from Table 6, our EV class also includes a much broader range of variables and probably runs deeper than just early adopters.

The parameter estimates and odds ratios for the class membership model are shown in Table 6. The parameters for the GV-oriented class are normalized to zero, so the estimated parameters refer to the EV-oriented class. They represent the impact of an attribute on the probability of being EV-oriented. For example, the positive and significant parameter for young indicates younger respondents (18–35) are more likely to be EV-oriented than older respondents (56 and above). The EV-oriented weights (probability of being in the EV-oriented class) ranged from as low as 6% to as high as 94% with a sample mean of 54%. Table 6 shows that the following variables increase a respondent's EV-orientation with statistical significance.

- Being younger or middle age
- Having a BA or higher degree
- Expecting higher gasoline prices in the next 5 years
- Having made a shopping or life style change to help the environment in the last 5 years
- Likely to buy a hybrid gasoline vehicle on their next purchase
- Having a place they could install an EV electrical outlet at home
- Likely to buy a small or medium-sized passenger car on next purchase
- Having a tendency to buy new products that come on to the market
- Taking at least one drive per month longer than 100 miles

The first eight were expected. The ninth, taking one or more frequent long drives a month, is counterintuitive. We expected that people making more long drives would be less inclined to buy an EV due to limited driving range and slow refueling. This result, which we also saw in some of our pretests, may come from an interest in saving fuel. People traveling longer distances pay more for fuel and stand to save more from EVs.

The odds ratios shown in Table 6 give the relative odds of a person being in one class versus the other for a given attribute. For example, the odds ratio of 1.3 for a middle-aged driver indicates that a person between 35 and 56 is 1.3 times more likely to be EV-oriented than a person over 56. The largest odds ratios are 3.3 for having a place for an electric outlet where they park, 2.9 for people who have recently made a major change in their life style to help the environment, and 2.3 for being a likely purchaser of a hybrid gasoline vehicle. The finding on hybrids suggests that EVs will compete with hybrids more than with conventional gasoline vehicles.

Contrary to expectations, income and being a multicar household both reduced the likelihood of being in the EV class, rather than increasing it, although without statistical significance. Analysts have assumed that multicar households are more amenable to EVs than single car households. In fact, the early EV market studies sampled only multicar households (Beggs et al., 1981; Calfee, 1985; Kurani et al., 1996). The logic for this stems from the fact that EVs have limited driving range and multicar households would not be constrained by this since they have a reserve car. Our data provide no evidence to support this assumption. Ewing and Sarigollu (1998) had a similar result.

[10] Following Swait (2007), these measures are defined as: $\mathrm{AIC} = -2(\mathrm{LL}(\boldsymbol{\beta}) - K)$ and $\mathrm{BIC} = -2\mathrm{LL}(\boldsymbol{\beta}) + K \times \log(N)$, where $\mathrm{LL}(\boldsymbol{\beta})$ is log likelihood value at convergence, K is the total number of parameters estimated, and N is number of observations. The class size that minimizes the BIC and AIC is the preferred class size.

Finally, we tested for regional differences in preference for EVs. We divided the United States into 10 regions. California and Florida were each treated as their own region. When we included only regional dummies in our latent class model, California, Florida and the Northeastern United States were most EV-oriented, the Western and Midwestern states most GV-oriented. However, when the covariates shown in Table 6 are included in the model, the regional differences largely vanish suggesting that it is the characteristics of people, not where they are from, that predicts class membership. The regional results are not shown in our tables.

4.2. Random utility model

The vehicle attributes (Δp_i and $\mathbf{x}_i$) used in the random utility portion of our model are shown in Table 2. The model is shown in Table 7 along with a multinomial logit version for comparison. We assume price and fuel cost have a linear effect. All other attributes are specified as categorical variables based on Wald and likelihood tests that showed nonlinear versions give a better fit. For Table 7, the category exclusions or reference levels (required for identification) are the least favorable level in each case. We also tested for potential interaction of vehicle attributes with several demographic variables. Of those tested, only the interaction between price of EV and the price for the respondent's next vehicle was found to be significant. This is the only interaction we included in the model.[11]

Most of the parameters have expected signs. Also, the relative size of the parameters for the attributes specified as stepwise dummy variables perform as expected. For example, the coefficient estimates show a preference ordering for range that increases consistently with more miles. This basic step-wise consistency holds for all attributes across the two classes. Finally, the coefficient on price is statistically significant and negative in all instances. Vehicle price is clearly an important predictor of EV choice, as one would expect.

The LC model has a higher likelihood than the MNL model and, when tested, is statistically preferred. The LC model is also preferable to the MNL model because there is considerable heterogeneity in the data. Also, several of the parameters that are significant in the MNL model are only significant for one class in the LC model. In a few cases, the differences in the parameters across the two classes are sizable and significant. A good example of this is fuel saving. It is significant in the MNL model, but significant only in the EV-oriented class of the LC model.

The last three columns of Table 7 are implicit values for the attributes. These values are computed by simply dividing the attribute coefficient estimate by the coefficient estimate of price within each class.[12] The third of these three columns is a probability weighted average for the two classes.

The coefficient estimate on the EV dummy variable, a key variable defining our two classes, indicates a wide separation in willingness to pay for EVs. The value represents the premium a respondent would pay or compensation a respondent would ask for to switch from a GV to an EV version of his/her preferred vehicle with base level attributes ignoring any adjustment for fuel cost (continuous variable in the model). The EV-oriented class would pay a premium of \$2357, while the GV-oriented class would ask for compensation of \$22,006. The weighted average is compensation of \$7060. This is sensible, given that the base-level EV attributes were the least desirable (75 miles range, 10 h to charge, etc.). The compensation or premiums for differing EV types including adjustments for fuel cost are presented in the next section.

Another difference between the two classes is in the value of fuel saving. The EV-oriented is more fuel conscious than the GV-oriented. The EV-oriented portion has a willingness to pay of \$4853 for each \$1.00/gallon reduction in fuel cost equivalent. The GV-oriented portion has a willingness to pay of only \$499 per \$1.00/gallon cost reduction, a value based on a parameter that is not statistically different from zero. This finding makes sense. Respondents showing a greater interest in EV put more weight on fuel economy. This is also consistent with our class membership model where the EV-oriented expect higher gas prices and hence greater concern for fuel saving. The weighted average

[11] Among the interactions tested were: range and annual miles driven, range and multicar household, range and driving more than 100 miles a day, fuel cost and annual miles driven, fuel cost and expected gas price, pollution and changes in life style.

[12] Since we include an interaction of price difference times expected vehicle purchase price, we actually divide by an amount adjusted for expected price. The results shown in the table are means for our sample.

Table 7
Random utility model and wtp estimates (*T*-stat. in parenthesis).

	Parameters			Implicit attribute values[a]		
	MNL model	Latent class model		Latent class model		
		GV-oriented class	EV-oriented class	GV-oriented class	EV-oriented class	Weighted average
EV constant	−2.5	−7.46	0.54	−$22,006	$2357	−$7060
	(−12.3)	(−4.9)	(4.3)			
Yea saying tendency	−0.28	−0.25	−0.37			
	(−4.5)	(−1.1)	(−4.6)			
Price relative to preferred GV (000)	−0.09	−0.339	−0.102			
	(−12.2)	(−3.0)	(−18.0)			
Price relative to GV × car price (000,000)	0.0007	0.0021	0.0012			
	(2.7)	(0.62)	(5.6)			
Fuel cost ($/gall)	−0.21	−0.169	−0.35	−$499[b]	−$4853	−$2706
	(−5.0)	(−0.72)	(−9.8)			
Driving range on full battery (excluded category is 75 miles)						
150 miles	0.49	1.32	0.53	$3894[b]	$7349	$5646
	(6.8)	(1.8)	(9.0)			
200 miles	0.77	1.94	0.92	$5723	$12757	$9289
	(11.3)	(2.7)	(15.9)			
300 miles	1.00	2.6	1.28	$7670	$17,748	$12,779
	(13.6)	(3.7)	(19.2)			
Charging time for 50 miles of driving range (excluded category is 10 hours)						
5 h	0.19	1.6	0.07	$4720	$971[b]	$2136
	(2.8)	(2.9)	(1.3)			
1 h	0.48	2.0	0.55	$5900	$7626	$5858
	(7.6)	(4.0)	(10.1)			
10 min	0.67	2.2	0.80	$6490	$11,093	$8567
	(10.7)	(4.2)	(14.9)			
Pollution relative to preferred GV (excluded category is 25% lower)						
50% lower	0.07	0.75	0.12	$2212[b]	$1664[b]	$1935
	(1.1)	(1.6)	(1.9)			
75% lower	0.10	0.90	0.19	$2655	$2635	$2645
	(1.6)	(2.5)	(3.2)			
95% lower	0.35	1.2	0.37	$3540	$5130	$4346
	(5.2)	(3.1)	(6.2)			
Acceleration relative to preferred GV (excluded category is 20% slower)						
5% slower	0.15	1.1	0.15	$3245[b]	$2080	$2655
	(2.4)	(1.4)	(2.8)			
5% faster	0.36	1.97	0.33	$5811	$4576	$5186
	(5.2)	(2.4)	(5.3)			
20% faster	0.55	2.2	0.59	$6490	$8181	$7348
	(8.0)	(2.5)	(9.6)			
Log likelihood value	−5356	−4929				
Sample size	6032	6058				

[a] Yea-say correction turned on in all cases.
[b] Based on a statistically insignificant parameter at the 5% level of confidence.

value across the two classes is $2706. The average respondent appears to be capitalizing about 5 or 6 years of fuel savings into their vehicle purchase. Assuming that a car is driven about 12,000 miles/year at the US car average of 24 miles/gallon, each $1.00/gallon reduction in cost is worth about $500 of fuel savings per year.[13]

[13] During our survey the retail price of regular gasoline was about $2.80 per gallon and electricity was at about $1.00 per "gallon" (6.25 kWh/0.85 × 13¢/kWh). Assuming 4 kWh per mile for an electric sedan and 85% efficiency to fill up, fuel savings would be about $900 per year for buying electric versus gasoline.

Considering the weighted results for the other EV attributes in Table 7, the driving range increments have the highest value, followed by charging time, performance, and pollution reduction. These are all relative to the baseline attribute values indicated in the table. To the weighted average respondent, increasing range from 75 to 150 miles is worth over \$5600. Increasing it from 75 to 200 is worth over \$9200, and from 75 to 300 miles over \$12,700. Note that the values increase at a decreasing rate. The per-mile incremental values are \$75/mile (75–150 mile range), \$73/mile (150–200 mile range), and \$35/mile (200–300 mile range).

For charging time, on average, respondents valued the initial improvement, a reduction from 10 to 5 h, at more than \$2000. Going from 10 h to 1 h is worth nearly \$6000, and going from 10 h to 10 min is worth about \$8500. The per-hour incremental values are \$427/h (10–5 h range), \$930/h (5–1 h range), and \$3250/h (1 h–10 min range).

Improving vehicle performance from 20% slower to 5% slower than a person's preferred GV, is worth about \$2600 using the weighted values. Increasing from 20% slower to 5% faster and to 20% faster are worth about \$5100 and \$7300. Better performance, defined here as faster acceleration, noticeably increases the value of an EV.

Finally, pollution reduction has the lowest values of the attributes included. With a 25% reduction over their preferred GV as a baseline and using the weighted values, people valued a 50% pollution reduction at about \$1900, a 75% reduction at about \$2600, and a 95% reduction at over \$4300. The incremental values for going to 50% are not statistically significant. The EV-oriented class has higher value for moving to 95% lower while the GV-oriented has higher value for moving to 50% lower. Both classes have similar value for moving to 75% lower.

5. Willingness to pay for different EV configurations

In this section we calculate respondents' willingness to pay (wtp) for several combinations of electric car attributes (more precisely, for several differing electric versions of their preferred gasoline vehicle). We then compare wtp with a simple projection of the added cost of producing electric versus gasoline vehicles. Since future costs and EV configurations are imprecise projections from current costs, trends, and technology opportunities we will present a range of estimates. We will also present a 'test' of the model that estimates the wtp for an EV with attributes equivalent to the attributes of a GV. We use these results to calibrate our estimates.

A person's wtp for an EV conditioned on being in class c is the amount of money that makes the person indifferent between an EV of a given configuration and a GV. In our model that is the value of Δw that solves the following equation within a given class

$$\beta_p \Delta w + \boldsymbol{\beta}_x \boldsymbol{x}_i + \varepsilon_i = \varepsilon_0 \quad \text{or} \quad \Delta w = \frac{-\boldsymbol{\beta}_x \boldsymbol{x}_i + (\varepsilon_0 - \varepsilon_i)}{\beta_p} \tag{4}$$

Since no person belongs entirely to one or the other class in our model and is instead part EV-oriented and part GV-oriented, we use the following weighted average in our calculation for each respondent

$$\Delta w_{\text{weighted}} = p_{\text{ev}} \Delta w_{\text{ev}} + (1 - p_{\text{ev}}) \Delta w_{\text{gv}} \tag{5}$$

where p_{ev} is probability of being in the EV-oriented class. Boxall and Adamowicz (2002) and Wallmo and Edwards (2008) use this formulation. Again, in our model, estimates for the probability of being EV-oriented (p_{ev}) range from 6% to 94%.

We begin with the 'test' of our model. We constructed an EV that more or less mimics a contemporary GV. Driving range is 300 miles, charging time is 10 min, pollution removal is 0% changed, performance (acceleration) is the same, and fuel cost is \$2.80/gal. Fuel cost and pollution are the only attributes outside the range of our data in this simulation, and neither is far outside the range. In our survey, the closest to 0% change in pollution offered was 25% reduction and the highest EV fuel cost offered was \$2.00. We used a simple linear projection for these attributes to extrapolate to 0% change and \$2.80/gal. We simulated the model only over the sample of respondents expecting gas prices to be in the range of \$2 to \$4 over the next 5 years.

If our model is a good predictor of the total value of an EV, one would expect the wtp for this EV to be near zero at least for the median person. That is, if people bought EVs based only on their attributes, buyers would be indifferent between an EV and GV with nearly equivalent attributes.[14]

We have to be careful. There will be some people who are willing to pay more and some less for an EV with nearly equivalent attributes to their preferred GV. For example, we included a set of questions leading up the choice experiment that asked people to indicate which attributes might matter to them in making an EV purchase. The purpose was to get people thinking about the attributes of EVs before making a choice. While being far from a commitment, the results suggest what might drive preferences and what might lead to wtp for EVs diverging from wtp for like GVs. For example, 64% of the respondents indicated that 'lower dependence on foreign oil' mattered a lot; 47% reported that 'avoiding trips to the gas station', mattered a lot, and 30% reported that 'interesting new technology' mattered a lot. For these fractions of the sample at least, this suggests wtp's for EVs would be above a like GV. Of course, saying that certain attributes matter and actually being willing to pay for them can be quite different. Also, there is an obvious free-rider problem with 'lower dependence on foreign oil'. If everyone else buys EV, I can enjoy the security without having to pay myself. If everyone behaves as such, EV purchases for the purpose of lowering oil dependence would be limited even if many consider it important.

There will also be respondents who require compensation for an EV equivalent to their preferred GV. There is the simple inertia of staying with what you know and some may not trust a new technology. Approximately 33% of the sample said 'unfamiliar technology' mattered a lot in thinking about buying an EV.

When we simulate the model for the test EV, we find a median wtp of \$3023 over a GV. That is, over half of the respondents are willing to pay more than \$3000 extra for an EV. As mentioned above, this could be due to a desire to purchase an EV beyond its specific attributes, due to conspicuous conservation, or due to some lingering SP bias in our data. To be on the conservative side, we treated this as SP 'hypothetical bias', and recalibrated our model to generate a wtp median value of zero for an EV with attributes comparable to a GV. This amounted to adjusting the alternative specific constant on the two EVs in our model until the median wtp for the test vehicle is zero. This more or less follows an approach suggested by Train (2009, pp. 66–67) in a somewhat different context and gives us a model with half of the sample willing to pay more for an EV equivalent to a GV, and half willing to pay less. The spread using the calibrated model for the middle 50% of the population (from the 25th to the 75th percentile) is −\$1816 to \$3178 with a median value of \$0. This model preserves the trade off among attributes in our model discussed in the previous section.

We considered six hypothetical EV configurations in our wtp estimation. All configurations are within the range of our data. Table 8 shows the assumed levels for each configuration where A is the least desirable and F is the most desirable. Table 9 shows the wtp estimates for each. While our six EV configurations are not real vehicles, actual vehicles are likely to fall in our range of attribute combinations A through F. For comparison, Table 10 describes attributes of electric vehicles that are on sale, available in prototype, or announced for production, and categorizes them as being closest to one of our six hypothetical EV configurations.

Fig. 2 is a box-and-whisker plot of our calibrated wtp for the six configurations over our sample of respondents. The bundles of EV attributes become more desirable as we move from left to right in the graph. Thus, the share of drivers willing to pay a premium increases as the attributes of the EV improve. The median wtp for our six configurations using the calibrated model ranges from −\$12,395 to \$9625. For configuration B (75 mi/5 h/50% lower pollution/5% slower/\$1 gal) the median wtp from the calibrated model is −\$8243 and the maximum over the sample is −\$4762. For configuration E (200 mi/1 h/50% lower pollution/20% faster/\$1 gal) the median wtp is \$6234 and maximum is \$12,820. So, our wtp estimates, as one would expect from the parameters estimated in our model, are quite sensitive to the vehicle's configuration of attributes. Fuel economy and performance play a critical role in these wtp estimates, not just whether the vehicle is "an EV". Consider configuration E. Driving range (200 miles) is worse than most GVs, and charging time (1 hour for 50 miles) is much longer than a

[14] If this is not the case, despite our efforts to purge the data of SP bias (respondents giving values that diverge from their true values because there is no actual commitment to purchase), some may remain.

Table 8
Attribute levels used to compose six hypothetical EV configurations.

EV scenario	Range (mi)	Charging time for 50 mi	Pollution (% lower)	Acceleration	Fuel cost ("Like $___/gallon")
A	75	10 h	25%	5% slower	$1
B	75	5 h	50%	5% slower	$1
C	100	5 h	50%	Same	$1
D	150	1 h	50%	5% faster	$1
E	200	1 h	50%	20% faster	$1
F	300	1 h	75%	20% faster	$1

Table 9
Calibrated wtp for six hypothetical EV configurations (2009 dollars).

EV scenario	Min	Q1	Median	Q3	Max
A	−$19,224	−$14,695	−$12,395	−$10,241	−$6919
B	−$12,597	−$9709	−$8243	−$6874	−$4762
C	−$9971	−$7075	−$5606	−$4234	−$2117
D	−$4714	−$523	$1604	$3598	$6671
E	−$1974	$3467	$6234	$8823	$12,820
F	$526	$6556	$9625	$12,497	$16,930

gasoline fill up. The other attributes (fuel economy, performance, and pollution reduction) are better than a GV. When we estimate wtp for configuration E using $2.80/gal gasoline equivalent, so there is no fuel saving over a conventional gasoline vehicle, the median wtp in the calibrated model falls from $6234 to $2439. When we change performance to the same level of a gasoline vehicle (fuel economy reset to $1.00/gal) the median wtp is $3419. And, when fuel economy and performance are both set to levels comparable to a gasoline vehicle, wtp is −$375. Fuel economy and performance are clearly important drivers of overall vehicle wtp.

Now we consider the added production cost of an electric versus gasoline vehicle and compare it to our wtp estimates for our six configurations. Our intention here is not to conduct a rigorous cost analysis, rather it is to make a rough approximation for comparative purposes. As an approximation, we consider only the incremental cost of the battery. This is because the electric motor, drive electronics, and charger are a little less expensive than the gasoline engine, fuel, and exhaust systems. Thus, to a first approximation, the cost differential between GV and EV is primarily the cost of the battery.

The Department of Energy's current cost estimates for its near term automotive battery 'goals' are:

- $1000/kWh (DOE stated current cost)
- $500/kWh (DOE goal for 2012)
- $300/kWh (DOE goal for 2014)

The second and third are goals established by the DOE as part of their Energy Storage R&D program (Howell, 2009). A recent interim technical assessment report by EPA, Department of Transportation, and California Air Board (2010) has similar per kWh cost projections for 2012 and 2015. Several industry sources also indicate that the above DOE goals and rate of change are approximately correct, as does an analysis of new EV offerings.[15]

We assume an EV fuel efficiency of 1 kWh for 4 miles of driving (e.g., 250 Wh/mile). The Nissan Leaf, for example, has a 24 kWh battery size and an advertised driving range of 100 miles. This translates to 4 miles/kWh. The Tesla Roadster has a 56 kWh battery and a driving range of around 220 miles, and

[15] For example, Tesla Automotive currently sells their 56 kWh battery pack for $36,000 or $642/kWh. The Nissan Leaf, with a 24-kWh battery has a retail price of $32,000; if we say this is $18,000 above a comparable gasoline car and the increment is attributed to the battery pack, it represents $18,000/24 kWh or $750/kWh for a 2010 model (www.nissanusa.com).

Table 10
Battery size, driving range, charging time, and price of some current EVs.

Vehicle	Battery	Range (mi)	Charging time (empty to full battery)	Charging time for 50 miles[a]	Expected date of release	Closest vehicle configuration for Table 9	Estimate of current base price
BMW Mini E	35 kWh lithium ion	156 mi	3 h at 240 V/48 A	58 min	Limited trial since 2009	D	$850/mo lease, incl. insurance
Coda Sedan	34 kWh	90–120 mi	<6 h at 240 V	2.5–3.5 h	Launch slated for late 2011	C	~$40,000
Ford Focus EV	23 kWh lithium ion	75 mi	6–8 h at 230 V	4–5 h		B	$35,000
AC Propulsion eBox	35 kWh	120 mi	2 h at 240 V	50 min	On sale since 2007 by custom order	D	N/A
Mitsubishi iMiEV	16 kWh	80 mi	7 h at 220 V	4.5 h	On sale in Japan	B	$47,000
Nissan LEAF	24 kWh	100 mi (city driving)	8 h at 220 V	4 h	On sale since December 2010	C	$33,000
Smart Fortwo ED	16.5 kWh lithium ion	85 mi	8 hrs at 230V	4 h	On sale in EU	A	$19,000
Tesla Model S	42 kWh standard	160 mi base model	3–5 h at 220 V/70 A, 80% charge in 45 min at 440 V	1–1.5 h	Deliveries scheduled to begin in 2012	D	$57,000
Tesla Roadster	56 kWh lithium cobalt	220 mi (combined city/HY)	3.5 h	<50 min	On sale since 2009	E/F	$109,000
Think City	24.5 kWh lithium ion batteries	112 mi for the U.S. market	8 h at 110 V	3.5 h	On sale in EU, initial deliveries to US December 2010	B	$38,000
Volvo Electric C30	24 kWh	93.2 mi	8 h at 230 V, 16 A	4.5 h	1000 vehicle consumer test in Fall 2011	B	N/A

Source: Josie Garthwaite, 2010, "Battle of the Batteries: Comparing Electric Car Range, Charge Times" on Gigacom, posted June 8, 2010, http://earth2tech.com/2010/06/08/battle-of-the-batteries-comparing-electric-car-range-charge-times/, corrected and augmented from our own testing, calculations, and communications with EV industry.

[a] When data were available, time required for a mid-state of charge 50 miles is used; when not available, full charge time is proportionally reduced to 50 miles. "Fast charge" with DC equipment is not included, as this infrastructure is not yet available.

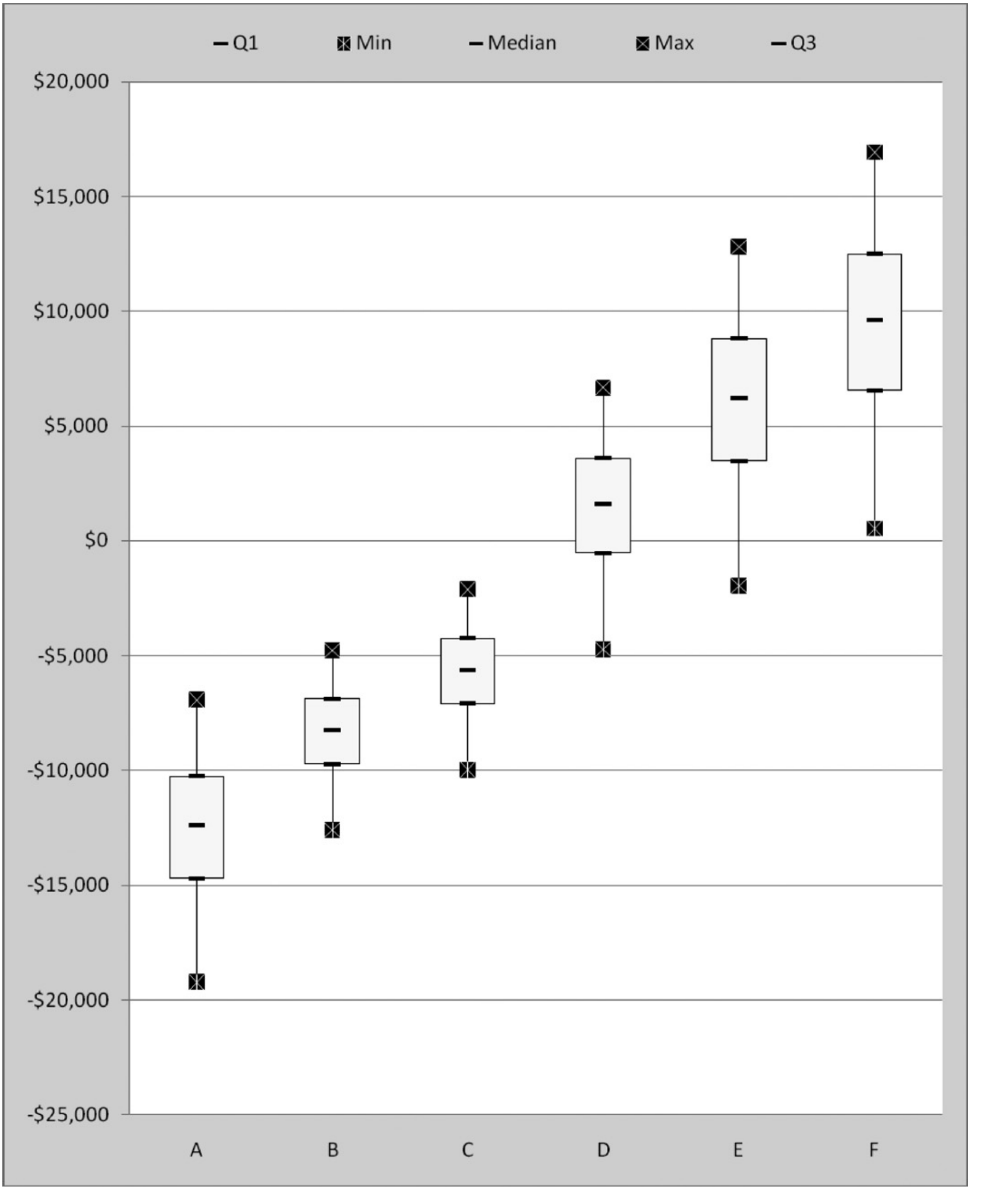

Fig. 2. Box–whisker plot of calibrated wtp for the six vehicle configuarations A–F, shown in Table 8.

this translates to 3.9 miles/kWh. These checks show 4 miles/kWh is reasonable for sedan-sized vehicles.

The three solid lines in Fig. 3 show the incremental cost per vehicle for each configuration using the three DOE battery cost estimates. Incremental costs range from $75,000 for a driving range of 300 miles at current battery costs to $5625 for a range of 75 miles if battery costs drop to $300/kWh. The two dashed lines are our estimated wtp for each configuration for the non-calibrated and

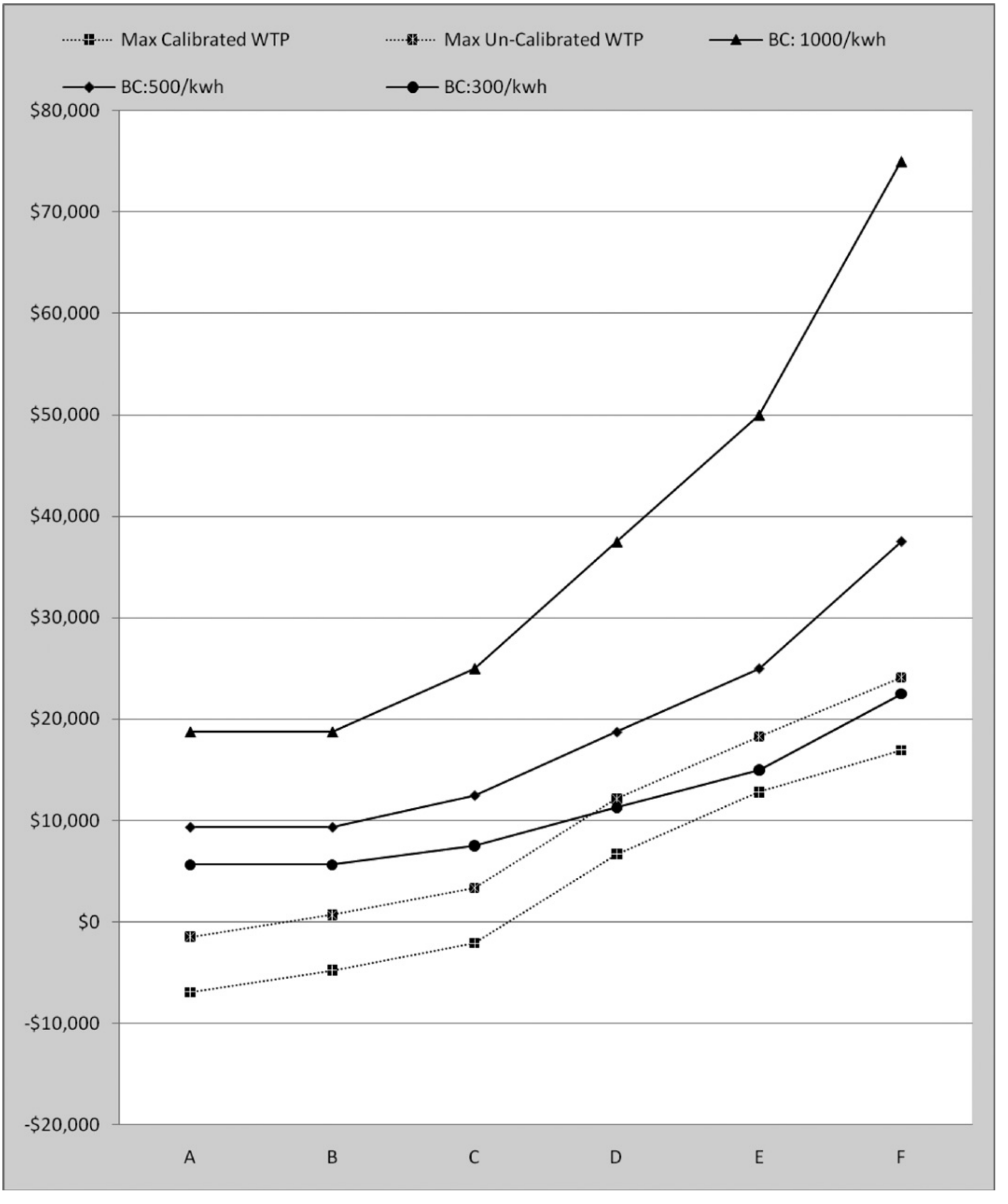

Fig. 3. Maximum wtp values (dotted lines) and estimated incremental vehicle costs (solid lines) for the six vehicle configurations.

calibrated versions of our model. *The lines are for the person in our sample with the maximum wtp* (see Fig. 2 for the full range of wtp below this line). The plots show a wide disparity between current battery costs and wtp. Current costs as stated by DOE are in every instance above maximum wtp. However, at the DOE projected cost of $300/kWh, the gap closes considerably and in some instances falls below the uncalibrated wtp suggesting EVs might be economic at lower costs. To get a sense of where the market is today see the rightmost column of Table 10.

There are a number of factors that could alter the position of either the cost or wtp lines in Fig. 2. First, there is the roughness of our cost estimates as discussed above. Second, our cost projections ignore technological developments for other aspects of EV production and the potential for savings through mass production of EVs and components. Third, we are assuming the cost of electricity stays at a level that keeps EV fuel costs at a $1.00/gallon equivalent. Fourth, we are not analyzing issues related to the life and disposal of the battery. Fifth, gasoline prices may rise or fall in a way unanticipated by our respondents. Sixth, if EVs make inroads in the market, infrastructure for charging at work, shopping centers and so forth are likely to be more accessible. (Although we asked respondents to assume such infrastructure existed, it is not obvious that they did.) Seventh, there is the prospect of vehicle-to-grid EVs producing revenue for drivers (Kempton and Tomić, 2005), making EVs more attractive to buyers. Eighth, the makers of GVs and other alternative fuel vehicles will not be dormant, they may introduce very small, more fuel-efficient vehicles to reduce the gap in cost-per-mile.

Finally, it is interesting to note that current US energy policy subsidizes the purchase of EVs with a tax credit of up to $7500/vehicle depending in part on battery size. A few states supplement this subsidy. California, for example, adds $3000 for a total of $10,500. Our analysis suggests that $7500 is sufficient to close the gap between wtp and vehicle cost for the DOE-projected $300/kWh case in Fig. 3.[16] That subsidy appears to be sufficient to stimulate market activity, given current and near future US costs of gasoline, electricity and EV batteries. Without the subsidy, our wtp analysis suggests that near-term purchase of EVs in the US would likely be limited.

6. Conclusions

Our analysis adds new insights into the demand for electric vehicles and confirms some earlier findings. We found that a person's propensity to buy an electric vehicle increases with youth, education, green life style, believing gas prices will rise significantly in the future, and living in a place where a plug is easily accessible at home. It also increases if a person has a tendency to buy a small or medium sized vehicle and/or is likely to be in the market for a hybrid vehicle for their next car purchase. Surprisingly, income and owning multiple cars were not important. We also found that people were driven more by expected fuel savings than by a desire to be green or help the environment. A reduction of one dollar per gallon of gas was worth about $2700 or five years of fuel cost saving.

Our analysis also confirmed some findings of earlier studies. We found that range anxiety, long charging time, and high purchase price remain consumers' main concerns about electric vehicles. For example, we find that individuals value driving range at about $35 to $75 per mile and charging time at about $425 to $3250 per hour.

Given the large push in favor of electric vehicles and the sizable investment of resources required to make such a transition, it is important to understand the market for EVs. It is surprising how little has been done on this front given the interest in the technology. Our analysis provides some guidance for both product attributes and consumer characteristics. Producers, for example, can gauge their own cost estimates for attributes like range or charging time against our wtp estimates for the same to judge where cost cutting is needed. For example, the wtp for a faster recharge ($5646 wtp to reduce 50 miles recharge from 10 h to 1 h) is a new finding of direct design relevance. In particular, one competing class of charger design achieves this charging time reduction by means of integrating the charging system into the drive system and does so at low marginal cost. Also, the current focus of R&D on improved batteries for more range makes sense based on our findings. Our results may also be used to target specific populations in marketing. For example, younger and educated populations are a good target, but income is probably less important than one might expect.

From a policy perspective we found that, despite the high premium some consumers are willing to pay for electric vehicles, battery costs need to drop considerably if EVs are to be competitive without subsidy at current US gasoline prices. At the same time we found that the current federal tax credit of

[16] Since vehicle cost exceeds unsubsidized wtp in our analysis, this subsidy is essentially passed on to the manufacturers of EVs since it will produce little or no reduction in the price of EVs on the market.

$7500 is likely to be sufficient to close the gap between costs and wtp if battery costs decline to $300/kWh (the cost level projected for 2014 by DOE).

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