

Willingness to Pay for Electric Vehicles and Their Attributes

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Abstract

This paper presents a stated preference study of electric vehicle choice using data from a national web-based survey. In our choice experiment respondents were asked to choose between two electric versions of their preferred gasoline vehicle and their preferred gasoline vehicle. The electric vehicles varied in attributes and price. The preferred gasoline vehicle was the opt-out alternative. Using the response data we valued five electric vehicle attributes: driving range, charging time, fuel cost saving, pollution reduction, and performance. Driving range, fuel savings, and charging time lead in terms of importance to respondents. Individuals were willing to pay (wtp) from \$35 to \$75 for a mile of added driving range, with wtp increasing at a decreasing rate with distance. They were willing to pay \$425 to \$3250 per hour of charging time (for a 50 mile charge), with wtp increasing at an increasing rate for shorter charges. Finally, people were capitalizing 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 substantial premium. At the same time, our results suggest that battery cost must drop significantly before electric vehicles are economic.

I. 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 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 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

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).

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 (EVs) rather than plug-in hybrid electric vehicles (PHEVs). 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 used data from a nationwide survey of potential car buyers in 2009. We offered people hypothetical electric versions of their preferred gasoline vehicle at varying prices and with varying features (eg, driving range and charging time). Then, using a latent class random utility model we estimated the demand for EVs. Based on these data, we identified two classes of drivers, which can be roughly labeled as EV-oriented and GV-oriented. Using parameter estimates from our model we then estimated respondents' willingness to pay (or willingness to accept compensation) to switch from their preferred gasoline vehicle (GV) to several hypothetical EVs. Finally, we compared these estimates to the corresponding incremental battery cost for converting a GV to the same hypothetical EV.

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 were interested in predicting the potential demand for EVs in California. Major among these were Bunch et al. (1993), Brownstone et al. (1996), and Brownstone and Train (1999). There were also some outside California including Tompkins et al. (1998), Ewing and Sarigollu (2000), and Dagviski et al. (2002). These studies differ from the earlier ones in many 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 an alternative substitute 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 especially Bunch et al., 1993; Tompkins et al., 1998; Ewing and Sarigollu, 2000). Table 1 is a summary of past EV studies for reference.

Our analysis builds directly on this body of work. Our model contributes to the literature by using more recent data, by using a method that focuses respondents on EV attributes (we offer respondents “EV-equivalents” of their preferred GV to control for extraneous features), by

estimating a latent class model, and by comparing willingness to pay or willingness to accept compensation estimates (wtp/wta) to battery cost projections.

The balance of the paper is organized as follows. Section II discusses our data and lays out our study design. Section III develops an econometric model for analyzing the data. Sections IV and V present the main findings, and Section VI concludes.

II. 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 conducted three focus groups and three pilot pretests. We also presented our study design at two academic workshops.² After each focus group and pretest, we refined the content and organization of the survey. Among the features adjusted were the description of the vehicles, amount and flow of information, length of the survey, and levels used for all vehicle attributes.

The final version of the survey had four parts: (i) background questions on present 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 in our hypothetical setting. The survey also included debriefing questions to get respondents' feedback regarding the relevance of each

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 Resource Economists Workshop: Energy and the Environment, June 18-10, 2009.

attribute in their choice and to ascertain the clarity and neutrality of the information provided on the survey. The vehicle-to-grid EV choice data from part (iii) are not analyzed in this paper.³

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 describing similarities and differences of EVs and GVs. Then respondents were asked two choice questions in a conjoint format. A sample question is shown in Figure 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 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 they had reported previously. Because the survey was web-based, the text of questions could include values from or be adjusted base 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. By holding these attributes constant, we were able 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 2.⁴

³ Vehicle to Grid (V2G) electric vehicles allow owners to sell their battery capacity to electric grid operators during times the vehicle is not driving, and thus have the potential of making EVs more economical (Kempton and Tomic 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.

⁴ 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.

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 focuses 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 gas”). This pretested far better than the other measures we considered and was independent of miles driven by the respondent.⁵ Pollution reduction was included as a measure of the desire to buy more environmentally beneficial goods. Finally, acceleration was included as a proxy for performance differences between EVs and GVs.

The choice sets were generated using efficient choice design (Kuhfeld et.al, 1994, Huber and Zwerina, 1996). We used a linear design to generate choice sets in a pilot study and then used the parameter estimates from the pilot study to generate our design (non-linear) for the final survey. We used SAS's choice macro function (Kuhfeld, 2005) to search for the efficient designs. Our experiment had a D-efficiency of 4.8. The design had 48 choice sets in 24 blocks. 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 Figure 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

⁵ 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.

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 include only US residents over 17 years old intending 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 in this group would be in the market for EVs. Our sample size was 3029. The sample was drawn from a panel of online respondents maintained by Sample Survey International (SSI). Use of this type of panel has the advantage that the respondents will answer questions administered by computer, but the disadvantage that panelists are those willing to do so repeatedly on a variety of topics. However, SSI will draw samples that are demographically representative of the US population. We were willing to accept the bias of a sample of people who can use computers because we thought few outside that category would buy an electric vehicle and it allowed us design our survey using an internet format and that was important for skip patterns and tailoring questions to respondent specific data such as car type on next purchase. We have provided descriptive statistics in Table 4. These include all of the demographic variables used in our model.

The sample was drawn from SSI to mirror the US population on census variables, apart from our prescreening criteria. As shown in Table 5, the sample is similar to the national census on most variables. We have nearly the same age distribution, income distribution and population size by region as the national census. Our sample somewhat under-represents men and less educated persons. The latter is probably due our prescreening exclusion of respondents purchasing cars less than \$10,000. Also, our sample is close to national statistics in the number of vehicles per household and ownership of residence even though the sample was not selected based on these criteria.

III. A Latent Class Random Utility Model

We estimated a latent class random utility model using our choice data (Swait, 1994)⁶. The random utility portion is a discrete choice model where respondents choose one of the three vehicles offered in our choice experiment – two electric and one gasoline. See the questions shown in Figure 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

$$\begin{aligned}
 U_i &= \beta_p \Delta p_i + \beta_x x_i + \varepsilon_i \\
 U_0 &= \varepsilon_0
 \end{aligned}
 \tag{1}$$

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

⁶ We compared mixed logit and latent class models (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.

The vector x_i includes all of the attributes used in the choice experiment: driving range, charging time, pollution reduction, performance, and fuel cost saving. Under the usual assumption of independent and identically distributed (iid) extreme value errors in (1), we have the following standard logit probability for vehicle choice for any given person

$$L(\beta) = \delta_1 \exp(\beta_p \Delta p_1 + \beta_x x_1) / I \\ + \delta_2 \exp(\beta_p \Delta p_2 + \beta_x x_2) / I \\ + \delta_0 / I$$

(2) where $\delta_1 = 1$ if the respondent chooses EV 1,
 $\delta_2 = 1$ if the respondent chooses EV 2,
 $\delta_0 = 1$ if the respondent choose GV,
 $I = 1 + \sum_{i=1}^2 \exp(\beta_p \Delta p_i + \beta_x x_i)$, and
 $\beta = (\beta_p, \beta_x)$.

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 β^c in equation (1). Class membership 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

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

where z = vector of individual characteristics,

(3) C is the number of latent classes,

$$\beta = (\beta^1, \dots, \beta^C),$$

$$\alpha = (\alpha^1, \dots, \alpha^C), \text{ and}$$

one α^c vector is arbitrarily set to zero for normalization.

The term $\frac{\exp(\alpha^c z)}{\sum_{c'=1}^C \exp(\alpha^{c'} z)}$ is the probability of membership in class c . $L(\beta^c)$ is the logit probability

from equation 2, now defined for class c . There are C sets of β^c and $C-1$ sets of α^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. Indeed, in our interpretation of the model, we assume no membership in any class. Rather, we assume each person has some weighted membership across classes. The parameters are estimated using maximum likelihood estimators and the number of preference groups is determined using a Bayesian Information Criterion (BIC). We will discuss these results and the BIC in the next section.

The LC model captures preference heterogeneity by allowing different preference orderings over the vehicles, with some classes having greater proclivity 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.

IV. Estimation Results

Latent Class Membership

The class membership portion of our model is shown in Table 6. Table 4 provides definition and descriptive statistics for all the variables used in the model. These are divided by variables pertaining to demography, driving distance, car type desired, gas price expectations, potential access for charger installation, and tendencies toward green lifestyle. 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., 2000, pp. 289). We computed information criteria (Bayesian and Akaike) for each latent class model.⁷ The Bayesian criterion selects a two-class model while the Akaike criterion selects a four-class model. We decided to use the two-class model. The preference classes divided neatly into a class of EV-oriented consumers and a class of GV-oriented consumers and interpretation of the parameters was clearer.

Santini and Vyas (2005) suggested two classes. What they refer to as an early group (a group that includes early adopters and early buyers), roughly corresponds to our EV class. These include consumers interested in EVs either because they are fascinated with the technology or because they want to help the environment (or reduce dependence on oil) and consumers

⁷ Following Swait (2007), these measures are defined as follows: $AIC = -2(LL(\beta) - K)$ and $BIC = -2LL(B) + K \cdot \log(N)$, where $LL(B)$ 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.

interested in EV to save fuel cost. Our model shows that a respondent has a greater EV orientation if, among other things, he or she is generally interested in new products, plans to buy a hybrid, has made changes in life style and/or shopping habit to help the environment, and expects gas prices to rise in the future.

The parameter estimates and odds ratios for the class membership model are shown in Table 6. The parameters are normalized to the GV-oriented class, so the parameters are interpreted as the probability of being EV-oriented versus GV-oriented or a person's EV-oriented weight. The results show that the following variables increase a respondent's EV-orientation with statistical significance

- Being younger
- Expecting higher gas prices in the next 5 years
- Having made a shopping/life style changes to help the environment in the last 5 years
- Likely to buy a hybrid gasoline vehicle on their next purchase
- Having a place to install an EV 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
- Having at least 1 drive per month longer than 100 miles
- Being male

The first seven were expected. The next, having one or more frequent long drives a month, was unexpected. We had thought that people making more long drives would be less inclined to buy an EV due to issues related to driving range. This result, which we also saw in some of our pretests, may come from an interest in saving fuel. People traveling further distances pay more for fuel and stand to save more from EVs. Also, our variable for number of long drives does not measure a person's average daily driving distance. We had no expectations on the sign for gender, and found, all else constant, that men are more EV-oriented.

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 2.2 for a young driver indicates that a person under 35 years old is 2.2 times more likely to be EV-oriented than GV-oriented. The highest odds ratios are 3.3 for having a place for an electric outlet at home, 2.9 for people having made a major change in their life style in the past 5 years to help the environment, 2.3 for being a likely purchaser of a hybrid gasoline vehicle, and 2.2 for being under 35 years old. The finding on hybrids is not surprising but reinforces the notion that EVs will compete with hybrids more than conventional gasoline vehicles.

Contrary to expectations, income and being a multicar household were not important predictors in our class membership model. Multicar households are generally perceived as more amenable to EVs than single car households. In fact, the early EV market studies sampled only multicar households (Beggs et al.1980, Calfee, 1985 and 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. We see no evidence to support this assumption. Ewing and Sarigollu (2000) had a similar result.

Finally, we tested for regional difference 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.

Random Utility Model

The vehicle attributes (Δp_i and 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 of the model 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. 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.⁸

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 as well as in the MNL model. Finally, the coefficient on price is statistically significant and negative in all instances. It is clearly an important predictor as one would expect.

The LC model has a higher likelihood than the MNL model and, when tested, is statistically preferred. The minimum, mean, and maximum probability of being EV-oriented are 6%, 53%, and 97%. So there is considerable heterogeneity in our data. Several of parameters that are significant in the MNL model are only significant for one class in the LC model. Also, in a

⁸ Among the interactions considered 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.

few cases the differences in the parameters across the two classes is sizable and significant. A good example of this is fuel saving (fuel cost). It is significant in the MNL model, but significant only in the EV-oriented portion 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 on price.⁹ The third of these three columns is a probability weighted average for the entire sample since each person has some positive probability of being in each class.

The coefficient estimate on the EV dummy variable, which is one of the key variables 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 their preferred vehicle with base level attributes ignoring any adjustment for fuel cost (continuous variable in the model). The EV-oriented portion of the model would pay a premium of \$2,357, while the GV-oriented portion would ask for compensation of \$22,006. The weighted average is compensation of \$7,060. The compensation/premiums for various 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 \$4,853 for each \$1.00/gallon reduction in fuel cost equivalent. The GV-oriented portion has a willingness to pay of only \$499 and that value is 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

⁹ Since we include an interaction of price difference times expected price, we actually divide by an amount adjusted for expected price using the respondent's expected price in each instance.

membership model where the EV-oriented expect higher gas prices and hence greater concern for fuel saving. The weighted average value across the two classes is \$2,706. 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.¹⁰

Considering the weighted results for the other conventional 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 baselines indicated in the table. To the weighted average respondent, increasing range from 75 to 150 miles is worth over \$5,600. Increasing it from 75 to 200 is worth over \$9,200, and from 75 to 300 miles over \$12,700. These high values are consistent with other findings that driving range is a critical attribute in EV purchase. Note that the values increase at a decreasing rate. The per-mile incremental values are \$75/mile (75 to 150 miles), \$73/mile (150 to 200 miles), and \$35/mile (200 to 300 miles).

The average weighted values are computed for charging time for 50 miles of driving. Using the weighted averages, respondents value the initial increment, a reduction from 10 to 5 hours, at over \$2,000. Going from 10 hours to 1 hour is worth nearly \$6,000, and going from 10 hours to 10 minutes is worth about \$8,500. Unlike the driving range values these increase at an increasing rate. The per-hour incremental values are \$427/hour (10 to 5 hours), \$930/hour (5 to 1 hour), and \$3,250/hour (1 hour to 10 minutes).

The value of pollution reduction is the lowest 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 \$1,900, a 75% reduction at about \$2,600, and a 95% reduction

¹⁰ 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/.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.

at over \$4,300. 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.

Finally, improving vehicle performance from 20% slower to 5% slower than a person's preferred GV, is worth nearly \$2,600 using the weighted values. Increasing to 5% and 20% faster from 20% slower is worth about \$5,100 and \$7,300.

V. Willingness to Pay for Different EV Configurations

In this section we calculate respondents' willingness to pay (wtp) or willingness to accept compensation (wta) for various electric versions of their preferred gasoline vehicle, and then compare these values to some projections of the added cost of producing electric versus gasoline vehicles. Since future costs and EV configurations are largely speculative, we will present a range of estimates. We will also present a 'test' of the model that estimates the wtp/wta for an EV with attributes equivalent to the attributes of a GV. We use these results to calibrate one set of estimates.

A person's wtp/wta 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

$$(4) \beta_p \Delta w + \beta_x \mathbf{x}_i + \varepsilon_i = \varepsilon_0 \quad \text{or} \quad \Delta w = \frac{-\beta_x \mathbf{x}_i + (\varepsilon_0 - \varepsilon_i)}{\beta_p}$$

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

$$(5) \quad \Delta w = p_{ev} \Delta w_{ev} = (1 - p_{ev}) \Delta w_{gv}$$

where p_{ev} is probability of being in the EV-oriented class. Boxall and Adamowicz (2002) and Walmo and Edwards (2008) use this formulation.

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 minutes, 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. The lowest pollution level offered was 25% removal and the highest fuel cost was \$2.00. We used a simple linear projection for these attributes to simulate in these ranges. 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 five years. If our model were a good predictor, one would expect the wtp/wta for this EV to be near zero at least for the median person. That is, on average we expect people to more or less be indifferent between an EV and GV with nearly equivalent attributes. If not, 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.

We have to be careful. There will, no doubt 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 to 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/wta for like EVs and GVs diverging. 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 above a like GV. Of course, saying these things and actually being willing to pay for them can be quite different. Also, there is 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 has behaves as such, EV purchases for the purpose of lowering dependence would be limited to only a few even though many may consider it important.

There will also be respondents who require compensation for an EV equivalent to their preferred GV. There is the simple of 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. In any case, we expect some deviation for equivalent EV and GV vehicles due to preference variation.

When we simulate the model we find a median wtp of \$3,023 for an EV over a GV with like attributes. Over half of the respondents are willing to pay more than \$3,000. Given a sample with an average car purchase price of \$23,000 for their next vehicle and an income of \$60,000, these numbers suggest that there may be some lingering SP bias in our data. For this reason, we present two sets of wtp/wta estimates: standard and calibrated. For the standard estimates, we

accept the model in our previous section as is. For the calibrated estimates, we use the same model but calibrated it to generate median wtp values of zero for an EV with characteristics identical to each respondent's GV. This amounts to adjusting the alternative specific constant on the EVs in our model until the zero median result is achieved. This follows an approach suggested by Train (2009, p. 66-7) in a somewhat different context and gives us a model with half of the sample be 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 -\$1,816 to \$3,178 with a mean value of \$0. This model preserves the trade off among attributes in our model discussed in the previous section. In the spirit of allowing the reader to draw his/her own conclusions from the data we will present both the standard and calibrated estimates.

We considered six hypothetical EVs in our wtp/wta 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 standard and calibrated wtp/wta estimates for each. While actual configurations are uncertain, most are likely to fall somewhere in this range of attribute combinations. We report where current vehicles fall in our range of configurations in the second to last column of Table 10. This list is incomplete, but most fall in the B to D range.

Figure 2 is a box-whisker plot of standard wtp/wta for our six configurations over our sample of respondents. The EV attributes improve as you move from left to right in the graph. The share of drivers willing to pay a premium naturally increases as the attributes of the EV improve. The median wtp for our six configurations using the standard (calibrated) model ranges from -\$9,221 to \$14,164 (-\$12,395 to \$9,625). For configuration B

(75mi/5hrs/50%pollution/5%slower/\$1gal) the median wtp from the standard (calibrated) model is -\$5,070 (-\$8,243) and the maximum over the sample is \$687 (-\$4,762). For configuration E (200mi/1hrn/50%poll/20%faster/\$1gal) the median wtp is \$9,406 (\$6,234) and maximum is \$18,296 (\$12,820). So, our wtp/wta 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 an important role in these calculations. Consider configuration E. Driving range (200 miles) is worse than most GVs, and charging time (1 hour for 50 miles) is longer than a fill up. The other attributes (fuel economy, performance, and pollution reduction) are better. When we estimate wtp for configuration E using \$2.80/gal gasoline, so there is no fuel saving over a conventional gasoline vehicle, the median wtp in the standard (calibrated) model falls from \$9,406 (\$6,234) to \$5,614 (\$XXX). With performance set to the same level of a gasoline vehicle (fuel economy set at \$1.00/gal) the median wtp is \$6,592 (\$XXX). When fuel economy and performance are set to levels comparable to a gasoline vehicle, wtp is \$2,799 (\$XXX). Fuel economy and performance are obviously important drivers in our results.

Now we consider the added cost of producing an electric versus gasoline vehicle and compare it to our wtp/wta 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. Indeed, we only consider battery cost as it varies for different driving ranges. We ignore installation of the charger, the cost of boosting acceleration/performance, and differences in maintenance costs.¹¹ We also ignore the difference in the cost the electric versus gasoline

¹¹ Consumer Reports (Cars Blog 9/3/2010), for example, estimates that the simplest charging system for a Nissan Leaf is around \$2000. Boosting acceleration/performance is tricky to estimate. Once a battery is configured to operate at highway speeds, boosting acceleration/performance at the margin is not expensive. Given the value respondents place on acceleration/performance, this is an important finding. If EVs are successful, we would expect most, if not all, to be on the higher performance end. With respect to

motor, which probably favors electric. And finally, we ignore any relative cost differences that may arise for different vehicle sizes. While the list is long, battery cost is by far and away the largest factor that makes EVs more expensive than GVs. We hope our first cut encourages others with better knowledge of the cost structure to make further comparisons that embody these elements of cost.

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). We will use these DOE figures, although actual commercial products already sold are both above and below them. For example, looking at current vehicles, it appears that the GM Volt, a plug-in hybrid, at 20 kWh (only 10 kWh usable) is above the \$1000/kWh DOE "current cost", whereas the Leaf, Tesla, eBox and Think are already selling vehicles with apparent battery costs in the \$600-\$700/kWh range, which approach the DOE 2012 "goal".¹²

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 24kWh battery size and a driving range of 100 miles. This translates to 4 miles/kWh. The Tesla Roadster has 56kWh battery and a driving range of around 220 miles, and this translates to 3.9mi/kWh. So, our assumptions seem reasonable.

maintenance, EVs are generally believed to have lower maintenance costs, although there is the disposal and replacement of the battery to consider.

¹² This assumes no below cost introductory prices (cross subsidization) by producers to establish markets.

The three solid lines in Figure 4 shows the incremental cost per vehicle for each configuration using the three battery cost estimates. As shown, these range from \$75,000 for a driving range of 300 miles at current battery costs to \$5,625 for a range of 75 miles if battery cost drop to \$300/kWh. The two dashed lines are our estimated wtp/wta for each configuration for the standard and calibrated versions of our model. The lines are for the person in our sample with the maximum wtp (see the Figures 2 and 3 for the full range of wtp/wta below this line). The plots show a wide disparity between current battery costs and wtp. Current costs are in every instance above maximum wtp/wta. However, at the projected costs of \$300/kWh, the gap closes considerably and in some instances falls below the wtp suggesting EVs may be economic at these lower costs. Certainly, if battery costs should drop even further as some suggest, the prognosis using our results would look even more favorable for EVs.

Table 10 is a list of driving ranges and charging times for some EVs on, or nearly on, the market for comparison. The table includes configurations and prices posted in the popular press. We have also included our best guess as to where each vehicle would be classified on our set of configurations. This gives a good sense of where the market is today.

Our analysis comes with a usual set of caveats and should be used with caution. There are a number of factors that could alter the position of either the cost or wtp/wta lines. Here are a number to keep in mind when using our numbers. First, there is the roughness of our cost estimates that we have mentioned above. Second, our cost projections ignore technological developments for other aspects of EV production and the potential for large savings in through the mass production of EVs. Third, we are assuming the cost of electricity stays at a level that keeps EV fuel costs at a \$1.00/gallon equivalent. Forth, we are ignoring all 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 see dramatic improvement. (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, making EVs more attractive to buyers. Eighth, the makers of GVs and other alternative fuel vehicles will not be dormant. To the extent that respondents did not consider developments for these vehicles, our analysis will be in error. For example, more fuel-efficient GVs may be offered as alternatives to EVs in the future and respondents may have not considered such developments.

Finally, as part of its current energy policy, the US government subsidizes the purchase of EVs by a tax credit of \$7,500/vehicle. A few states supplement this subsidy, for example, California adds \$3,000.¹³ Our analysis suggests that \$7,500 is sufficient to close the gap between wtp/wta and cost for the \$300/kWh case in Figure 4.¹⁴ We are not taking a position here on whether or not such subsidy is good policy. We are only saying that our analysis suggests that the subsidy is sufficient to stimulate market activity, given current and near future US costs of gasoline, electricity and automotive batteries. Without it, near-term purchase of EVs in the US would likely to be limited.

Again, we consider this analysis entirely exploratory, intended to give the reader an idea of how our model may be used rather than drawing any specific conclusions. We hope the results are used in the light.

¹³ A recent New York Times article (October 7, 2010) list subsidies that could range as high \$13,000 per vehicle.

¹⁴ Since cost exceed wtp in our analysis, it is important to note that this subsidy is essentially passed onto the manufacturers of EVs since it will produce little or no reduction in the price of EVs on the market.

VI. Conclusions

Our analysis confirms and quantifies some of the variables from prior electric vehicle (EV) demand studies, while adding new quantitative variables and depth to understanding the wtp of multiple EV attributes. Quantifying the prior observation of “range anxiety”, we find that individuals are willing to pay anywhere from \$35 to \$75 for a mile of added driving range. They are also willing to pay \$425 to \$3250 per hour of charging time (for a 50 mile charge). They especially dislike slow charging time and short range in the extreme cases – 10 hours required to charge and 75 miles of range. This is true even for those most favorably disposed to EVs. Fuel savings by going electric, not surprisingly, matters and matters more to those most likely to be in the EV market. We find that the average individual capitalized about five years of fuel savings into the price of an EV. Considering the individual EV attributes, we found the most important to be (in order): range, charging time, performance, and pollution reduction. The value of fast charging and performance have not been well documented in the EV literature. We find, contrary to some prior assumptions, that EV purchase should not be thought of as primarily a “green” purchase—environmental concern has some effect, but other convenience and performance attributes are more important to wtp.

Considering demographics, we found that a person’s likelihood of purchasing an EV increases if they are young, male, expect gas prices to rise, live a green life style, plan to buy a hybrid vehicle as their next car, have a place for an EV outlet at home, tend toward smaller gas cars, and have frequent long drives. Frequent long drives was a surprise due to range limitations of current EVs, but may be explained by respondents’ motivation for fuel cost savings. Location (regions in the US) did not matter after we controlled for the attributes of the people.

We found that the people most interested EVs were willing to pay a substantial premium over equivalent GVs. For those in the top 10th percentile, willingness to pay for an EV with 150 miles driving range and 1 hour charging time per 50 miles driving range was about \$9,645 to \$4,953 more than an equivalent GV. Using a simple model of increased vehicle cost, estimated to be equivalent to battery cost at DOE projected cost levels, we found that battery costs need to drop considerably if EVs are to be competitive without subsidy and with current US gasoline prices. DOE has a 2014 goal for battery cost to decline to \$300/kWh. DOE-stated current cost is \$1000/kWh, although some manufacturers are already reaching \$600-700/kWh. We also find that the current federal subsidy of \$7500 is sufficient to close the gap between costs and wtp if battery costs decline to \$300/kWh.

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Table 1: Summary of Past EV Studies

Study	Econometric Model	Number of choice sets, attributes, & levels	List of attributes used
Beggs et al. (1981)	Ranked logit	16, 8, NA	Price, fuel cost, range, top speed, number of seats, warranty
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 vs multi-fuel capability
Brownstone and Train (1999)	MNL and Mixed logit	2, 13, 4	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
Brownstone et al. (2000)	Joint SP/RP Mixed logit	2, 13, 4	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 (2000)	MNL	9, 7, 3	Price, fuel cost, repair and maintenance cost, commuting time, acceleration, range, charging time
Dagsvik et al. (2002)	Ranked logit	15, 4, NA	Price, fuel cost, range, top speed

Table 2: Attributes and Levels Used in the Choice Experiment

Attributes	Levels
Price relative to your preferred GV	Same
	\$1,000 higher
	\$2,000 higher
	\$3,000 higher
	\$4,000 higher
	\$8,000 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 minutes,
	1 hour
	5 hours
	10 hours
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

Table 3: Distribution of Choices among Alternatives

Alternatives	Without yea-saying correction (%) N=1033	With yea-saying correction (%) N=1996
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

Table 4: Descriptive Statistics (N=3029) for variables used in LC Model. Either % or mean is shown, depending on whether the variable is dichotomous.

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)
Gas 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	

Table continued on Next Page.

Table 4: Descriptive Statistics (N=3029): continued

Variable	Description	% in sample	Mean (SD)
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	

Table 5: Comparing Sample and Census Data

Variable	Sample (%)	Census (%)
Male	43.0	48.7
Age distribution		
18 to 24	12.0	12.9
25 to 44	39.4	36.3
45 to 64	34.7	33.9
65 to 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
\$10k to \$14,999	3.3	5.5
\$15k to \$24,999	10.2	10.6
\$25k to \$34,999	13	10.6
\$35k to \$49,999	19.1	14.2
\$50k to \$74,999	22.5	18.8
\$75k to \$99,999	13.5	12.5
\$100k to \$149,999	10.3	12.2
\$150k to \$199,999	1.9	4.3
\$200k 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

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 ¹	0.81	6.1	2.2
Middle age ¹	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
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 ²	0.36	2.6	1.4
Medium car ²	0.23	2.3	1.3
Long drive	0.20	2.0	1.2
Major green ³	1.05	6.9	2.9
Minor green ³	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.

1. Excluded category is Old (>56)

2. Excluded category is Large car

3. Excluded category is Not green

Table 7: Random Utility Model and WTP Estimates (t-stat. in parenthesis)

Attributes	Parameters			WTP Values		
	MNL Model	Latent Class Model		Latent Class Model ¹		Weighted Average
		GV-Oriented Class	EV-Oriented Class	GV-Oriented Class	EV-Oriented Class	
EV constant	-2.5 (-12.3)	-7.46 (-4.9)	0.54 (4.3)	-\$22,006	\$2,357	-\$7,060
Yea saying tendency	-0.28 (-4.5)	-0.25 (-1.1)	-0.37 (-4.6)			
Price relative to preferred GV (000)	-0.09 (-12.2)	-0.339 (-3.0)	-0.102 (-18.0)			
Price relative to GV * car price (000,000)	0.0007 (2.7)	0.0021 (0.62)	0.0012 (5.6)			
Fuel cost (\$/gall)	-0.21 (-5.0)	-0.169 (-0.72)	-0.35 (-9.8)	-\$499 ²	-\$4,853	-\$2,706
Driving range on full battery (excluded category is 75 miles)						
300 miles	1.00 (13.6)	2.6 (3.7)	1.28 (19.2)	\$7,670	\$17,748	\$12,779
200 miles	0.77 (11.3)	1.94 (2.7)	0.92 (15.9)	\$5,723	\$12,757	\$9,289
150 miles	0.49 (6.8)	1.32 (1.8)	0.53 (9.0)	\$3,894 ²	\$7,349	\$5,646
Charging time for 50 miles of driving range (excluded category is 10 hours)						
10 minutes	0.67 (10.7)	2.2 (4.2)	0.80 (14.9)	\$6,490	\$11,093	\$8,567
1 hour	0.48 (7.6)	2.0 (4.0)	0.55 (10.1)	\$5,900	\$7,626	\$5,858
5 hours	0.19 (2.8)	1.6 (2.9)	0.07 (1.3)	\$4,720	\$971 ²	\$2,136
Pollution relative to preferred GV (excluded category is 25% lower)						
95% lower	0.35 (5.2)	1.2 (3.1)	0.37 (6.2)	\$3,540	\$5,130	\$4,346
75% lower	0.10 (1.6)	0.90 (2.5)	0.19 (3.2)	\$2,655	\$2,635	\$2,645
50% lower	0.07 (1.1)	0.75 (1.6)	0.12 (1.9)	\$2,212 ²	\$1,664 ²	\$1,935
Acceleration relative to preferred GV (excluded category is 20% slower)						
20% faster	0.55 (8.0)	2.2 (2.5)	0.59 (9.6)	\$6,490	\$8,181	\$7,348
5% faster	0.36 (5.2)	1.97 (2.4)	0.33 (5.3)	\$5,811	\$4,576	\$5,186
5% slower	0.15 (2.4)	1.1 (1.4)	0.15 (2.8)	\$3,245 ²	\$2,080	\$2,655
Log likelihood value	-5356		-4929			
Sample size	6032		6058			

1. Yea-say correction turned on in all cases.

2. Based on a statistically insignificant parameter at the 5% level of confidence.

Table 8: Attribute Levels Used for EV Configurations

EV scenario	Range (mi)	Charging time for 50 mi	Pollution (percent lower)	Acceleration	Fuel cost (“like \$ ___ per gallon”)
A	75	10 hours	25%	5% slower	\$1
B	75	5 hours	50%	5% slower	\$1
C	100	5 hours	50%	same	\$1
D	150	1 hour	50%	5% faster	\$1
E	200	1 hour	50%	20% faster	\$1
F	300	1hour	75%	20% faster	\$1

Table 9: Standard and Calibrated wtp/wta Values for Different EV Configurations (2009 Dollars)

EV scenario		Min	Q1	Median	Q3	Max
A	Standard	-\$18,875	-\$12,478	-\$9,221	-\$6,173	-\$1,469
	Calibrated	-\$19,224	-\$14,695	-\$12,395	-\$10,241	-\$6,919
B	Standard	-\$12,248	-\$7,488	-\$5,070	-\$2,288	\$687
	Calibrated	-\$12,597	-\$9,709	-\$8,243	-\$6,874	-\$4,762
C	Standard	-\$9,612	-\$4,855	-\$2,433	-\$166	\$3,333
	Calibrated	-9,971	-\$7,075	-\$5,606	-\$4,234	-\$2,117
D	Standard	-\$4,282	\$1,750	\$4,819	\$7,692	\$12,126
	Calibrated	-\$4,714	-\$523	\$1,604	\$3,598	\$6,671
E	Standard	-\$1,625	\$5,684	\$9,406	\$12,891	\$18,296
	Calibrated	-\$1,974	\$3,467	\$6,234	\$8,823	\$12,820
F	Standard	\$1,813	\$9,995	\$14,164	\$18,069	\$24,093
	Calibrated	\$526	\$6,556	\$9,625	\$12,497	\$16,930

Table 10: Driving Range and Charging Time for Some Current EVs

Vehicle	Battery	Range (mi)	Charging time (Empty to Full Battery)	Charging time for 50 miles	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 hrs at 240V/48 amp.	58 mins	Limited trial since 2009	D	\$850-\$600/mo lease include insurance
Coda Sedan	34 kWh	90-120 mi	<6 hours at 240V.	2.5-3.5 hrs	launch slated for late 2011	C	~\$40,000
Ford Focus EV	23 kWh Lithium ion	75 mi	6-8 hours at 230V	4-5 hrs		B	\$35,000
AC Propulsion eBox	35 kWh	120 mi	2 hours at 240V 80 amp	50 mins	Custom order	C/D	N/A
Mitsubishi iMiEV	16 kWh	80 mi	7 hrs at 220V, 2.5 hrs fast charge	4.5 hrs, 1.5 hrs	On sale in Japan	B	\$47,000
Nissan LEAF	24 kWh	100 mi (city driving)	8 hrs at 220V. 80% charge in 30 mins with fast charge	4 hrs	launch slated for the end of this year	C	\$33,000
Smart Fortwo ED	16.5 kWh lithium ion	85 mi	3.5-8 hrs, depending on starting charge level and voltage used	2 -5 hrs	On sale in EU	B	\$19,000
Tesla Model S	42 kWh standard	160 mi base model	3-5 hrs at 220V/70 amp, 80 percent charge in 45 mins at 440V.	1 – 1.5 hrs	Deliveries scheduled to begin in 2012.	D	\$57,000
Tesla Roadster	56 kWh lithium cobalt	220 mi (combined city/HY)	3.5 hours at high power	<50 mins	Out sale since 2009	E	\$109,000
Think City	24.5 kWh lithium ion batteries	112 mi for the U.S. market	8 hrs at 110V.	3.5 hrs	On sale in EU, being delivered to US fleets	B	\$38,000
Volvo Electric C30	24 kWh	93.2 mi	8 hrs at 230V, 16 amp	4.5 hrs	50-vehicle test fleet slated for Sweden	B	N/A

Source: [Josie Garthwaite](#), 2010, “Battle of the Batteries: Comparing Electric Car Range, Charge Times” on Gigacom, posted Jun. 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 and calculations, and from communications with EV industry.

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	Your Preferred Conventional Gasoline Vehicle
Driving Range on Full Battery	75 miles	150 miles	
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

Figure 1: Sample EV Choice Set

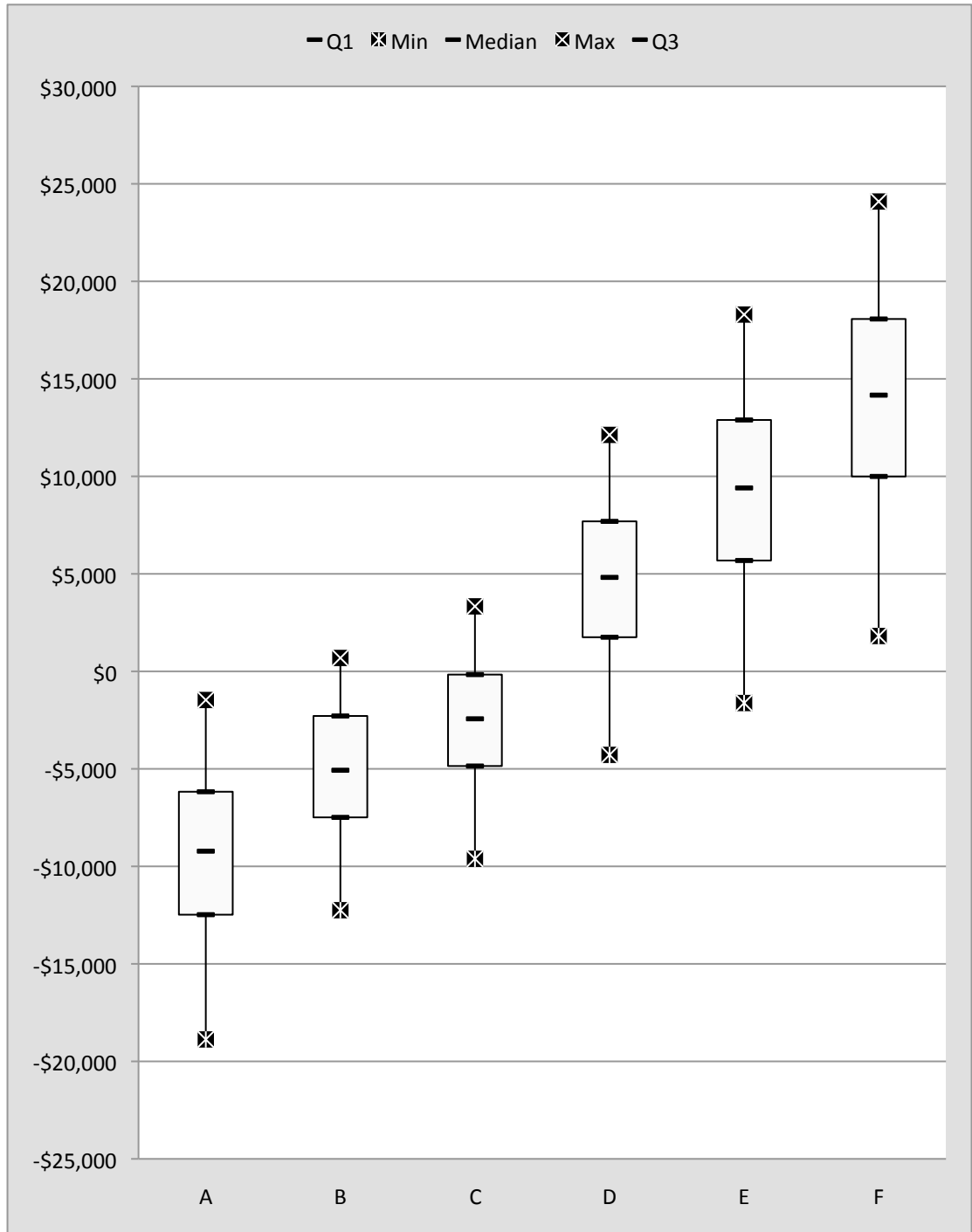


Figure 2: Box-Whisker Plots of Standard wtp/wta for six Vehicle Configurations Shown in Table 8

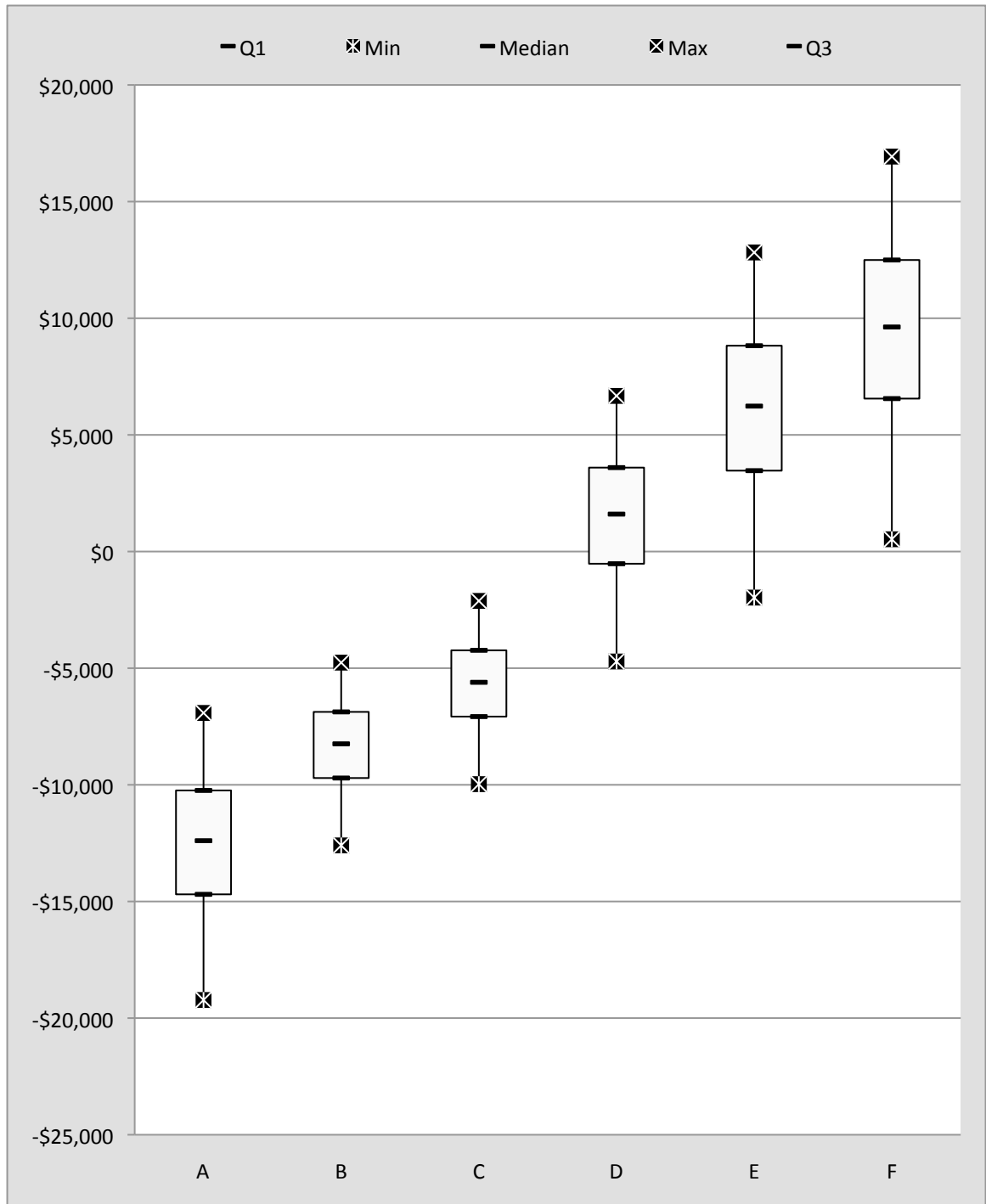


Figure 3: Box-Whisker Plots of Calibrated wtp/wta for six Vehicle Configurations Shown in Table 8

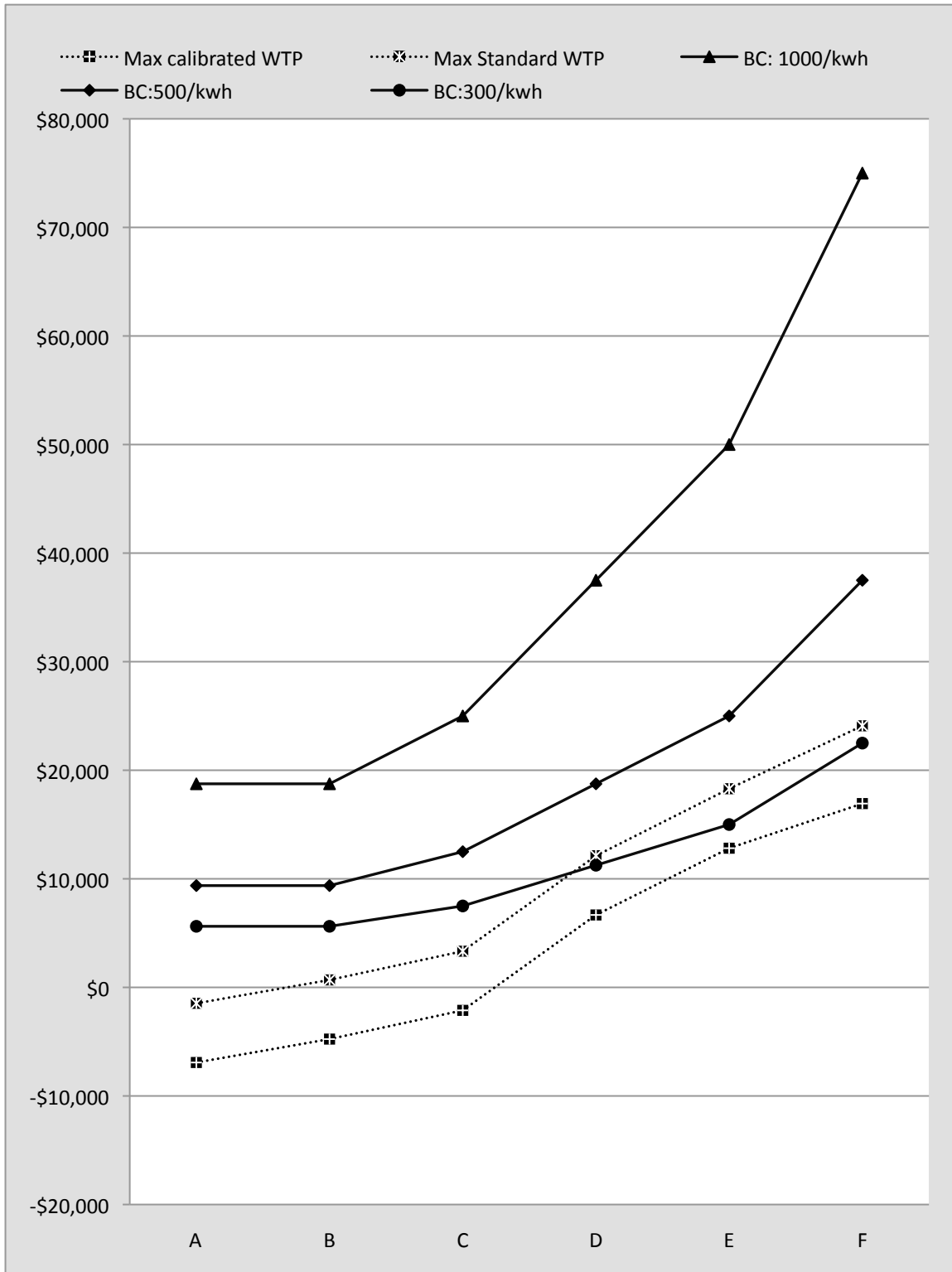


Figure 4: Comparing maximum WTP values and battery costs

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