WORKING PAPER NO. 2011-21

CAN VEHICLE-TO-GRID REVENUE HELP ELECTRIC VEHICLES ON THE MARKET?

By

George R. Parsons, Michael K. Hidrue, Willett Kempton, and Meryl P. Gardner

WORKING PAPER SERIES

UNIVERSITY OF DELAWARE | Alfred Lerner College of Business & Economics

DEPARTMENT OF ECONOMICS

Can Vehicle-to-Grid Revenue Help Electric Vehicles on the Market?

George R. Parsons, Michael K. Hidrue, Willett Kempton, and Meryl P. Gardner
University of Delaware
Newark, DE 19716

Abstract

Vehicle-to-grid (V2G) electric vehicles can return power stored in their batteries back to the power grid and be programmed to do so at times when power prices are high. Since providing this service can lead to payments to owners of vehicles, it effectively reduces the cost of electric vehicles. Using data from a national stated preference survey (n = 3029), this paper presents the first study of the potential consumer demand for V2G electric vehicles. In our choice experiment, 3029 respondents compared their preferred gasoline vehicle with two V2G electric vehicles. The V2G vehicles were described by a set of electric vehicle attributes and V2G contract requirements such as "required plug-in time" and "guaranteed minimum driving range". The contract requirements specify a contract between drivers and a power aggregator for providing reserve power to the grid. Our findings suggest the V2G concept is mostly likely to help EVs on the market if power aggregators operate on pay-as-you-go-basis or provide consumers with advanced cash payment (upfront discounts on the price of EVs) in exchange for V2G restrictions.

Key words: electric vehicles, vehicle-to-grid, stated preference, latent-class model

JEL classification: Q42; Q51

I. Introduction

Vehicle-to-grid (V2G) power is a new concept in electric vehicle design. It involves designing electric vehicles (EVs) so that they can discharge power stored in their batteries back to the electric grid. A grid-integrated vehicle with V2G capability has controls that enables it to charge/discharge economically – charge when electricity is cheap and discharge when expensive. The idea behind such a design is to use parked EVs as a source of reserve power to the electric grid. The electric grid uses reserve power to smooth fluctuation in power generation and to respond to unexpected outages. This is now done with large generators but may (in the future) also be done with EVs using the idle capacity in their batteries. The average US car is parked 95% of the time (Pearre, 2011). With proper technology, EVs may be able to provide reserve service at a lower cost and pay the owners of EVs for the service.[1]

Designing EVs with V2G capability has two advantages. First, payment to owners of EVs may help lower the overall cost of ownership of EVs, which is currently above the market price of gasoline vehicles (GVs). Kempton and Tonic (2005), for example, show a Toyota RAV4 EV can earn up to $2554 annually from providing reserve service to the electric grid. Second, designing EVs with V2G capability enhances the environmental benefits of EVs. V2G vehicles can replace generators currently providing reserve service. Depending on the type of fuel used by the generators, this may have net environmental benefits. V2G vehicles can also support renewable sources of energy such as wind and solar (Kempton and Dhanju, 2006). Wind and solar have larger fluctuations in output than conventional sources of energy due to natural causes and are hence in greater need of storage capacity. V2G vehicles

[1] For more on V2G electric vehicles see Kempton and Letendre (1997), Kempton et al (2001), and Kempton and Tomic (2005).

could be used for storage during periods of high output and for reserve power during periods of low output.

These benefits have already attracted the interest of policy makers and power companies. However, little is known about consumers' interest in such vehicles. Will consumers embrace the idea of re-selling power to power companies or aggregators of power? If so, at what price? Can revenue earned from such a plan help EVs on the market?

To answer these questions, we administered a web-based stated preference survey. A total of 3029 respondents randomly selected from a national sample completed the survey. The survey had two parts: a choice experiment for conventional electric vehicles with no V2G capability (hereafter C-EVs) and a choice experiment for V2G electric vehicles (hereafter V2G-EVs). We used data from the first choice experiment to estimate consumers' willingness to pay for C-EVs and their attributes in an earlier paper (Hidrue, Parsons, Kempton, and Gardner (2011)). This paper is a follow-up focusing on the V2G-EV choice data.

We used a latent class random utility model to analyze respondents' choice of V2G-EVs. The model allowed us to capture preference heterogeneity in the data. Our analysis indicates that consumer preference for V2G-EVs can be captured in two classes, which we label as EV-oriented and GV-oriented (gasoline vehicle) consumers. Respondents in the EV-oriented class have a higher proclivity toward V2G-EVs. To assess the impact of designing EVs with V2G capability, we simulated several contracts and estimated the payment (or cash back) that respondents would require to sign the contracts. The contracts included a minimum number of plug-in hours and a minimum guaranteed driving range. These features are required by power companies to have certainty about the availability of power from parked cars when needed. We found respondents associate high inconvenience cost with most contracts relative to the cash back provided. We also found respondents heavily discount future revenue offered in V2G contracts. Our analysis suggests that for the V2G concept to increase the value of EVs, power aggregators have either to eliminate V2G contracts (allow consumers to buy and sell at will) or provide cash payments in advance in the form of a reduction in the initial purchase price of the vehicle.

II. The Concept of Vehicle to Grid

As noted above vehicle to grid (V2G) power refers to the flow of power from electric vehicles back to the power grid. V2G-capable vehicles can be battery electric vehicles, plug-in hybrid electric vehicles, or fuel cell electric vehicles. In this study, we consider only battery electric vehicles.

The basic idea behind the concept of V2G is to use EVs as a source of reserve power while the vehicles are parked. The average US car is parked 95% of the time. Most of this time no charging is required, so the vehicle's electric system is unused. If EVs can be controlled by a grid operator, and if they can both charge and discharge on such a signal, this idle capacity can be used as reserve power to the electric grid. There are several markets for such power capacity, traded on wholesale markets by Transmission System Operators (TSOs), as well as additional uses of value to power distribution companies (electric utilities). Currently large generators are used for reserves. EVs can also provide these reserves and the revenue stream earned from providing these electric services may help offset the current high cost of electric vehicles.

The amount of revenue a V2G vehicle can earn depends on many factors including the length of time the vehicle is plugged in and hence available to provide reserve service, the size of the vehicle's battery, the power of the charger, the vehicle's daily drive, and the type of reserve market. Generally, the value of the reserve service is greater: the longer the car is available, the larger the size of the battery, the stronger the power of the charger, and the shorter the driver's driving requirements. The equations defining these quantitative relationships are formally derived in Kempton and Tomic (2005).

In most TSO markets, the highest value markets for a V2G-EV are the ancillary services markets (A/S), called spinning reserves and regulation. Spinning reserves refers to a reserve generation capacity that is running and synchronized with the electric grid. This reserve is used when there is a sudden power interruption, for example from equipment failure. It is rarely used (typically 30 times per year for 5-10 minutes per call) but has to be ready on standby 24 hours a day, 7 days a week. Regulation reserve refers to a reserve capacity required to regulate frequency fluctuations. To maintain quality, generation and load must always be equal. However, in reality these two are rarely equal. Power companies smooth the difference by maintaining a regulation reserve capacity from which they can draw when there is an excess load (regulation up) and to which they can dump when there is an excess generation (regulation down). Regulation is called frequently to make small adjustments, typically hundreds of times per day. Like spinning reserve, regulation has to be available 24 hours a day, 7 days a week.

Spinning reserve and regulation are paid by capacity (kW), that is, they are paid by the maximum amount of power available. These markets pay much less for actual transfer of energy (kWh) than for capacity. In fact, for new V2G markets, the energy payment for V2G may not be included. This means, a V2G-EV would be paid for the time the vehicle is available to provide the service, regardless of whether or not power is consumed. Spinning reserve and regulation together have an annual market value of

$12 billion (Kempton and Tomic, 2005). Because A/S markets like spinning reserves and regulation are wholesale, many vehicles must be aggregated by a service provider who would collect power capacity from individual cars and sell the aggregate power capacity to TSOs or other electric grid market participants. Here we are primarily concerned with the relationship between the aggregator and the individual V2G-EV owners.

The relationship between the aggregator and the V2G-EV owner may take either a contractual form or a non-contractual form. In the former, drivers would sign a contract with aggregators and get paid accordingly. Under this system, drivers have an obligation to make their cars available for providing reserve service for a specified number of hours per day or month. In the latter, drivers would have no obligation to provide reserve service. They would be paid on a pay-as-you-go basis for the capacity they provide. The advantage of a contract, which is the most widely discussed approach, is that it provides more assurance of power capacity to the aggregator, and consequently also makes it possible for the aggregator to make up-front payments or investments in the customers' facilities. In this study, we follow a business model assuming a contract, similar to that discussed in Kempton and Tomic (2005) where each V2G vehicle owner signs a contract with a power aggregator.

III. Survey Design

We conducted a national web-based stated-preference survey in 2009. The survey included two choice experiments: one covering the choice of C-EVs and focusing on their attributes vis-à-vis GVs and another focusing on V2G-EVs and their contract terms. Details about the design of the survey, sample selection, and characteristics of the data can be found in Hidrue, Parsons, Kempton, and Gardner (2011) -- hereafter referred to as HPKG 2011.

We purposely divided the survey into two separate sets of choice experiments to improve respondent comprehension of V2G-EVs and to simplify the V2G-EV choice experiment. Describing C-EVs alone was complicated, and we felt that including V2G attributes simultaneously was too much. The first part of our survey, pertaining to C-EVs, described and compared C-EVs to gasoline vehicles (GVs). Respondents were given a choice experiment in which they made a choice between their preferred GV and two C-EVs of similar configuration (see Figure 1). This exercise familiarized people with the C-EVs and their attributes that differentiated them from GVs – charging time, driving range, fuel saving, performance, and reduction in pollution. Then, with a basic understanding of C-EVs and the choice experiment process, we introduced the V2G-EV concept and a V2G-EV contact.

We described how the buyer could charge or discharge the battery and get paid for selling power back to the company but would be required to have the vehicle plugged in and available to discharge power a fixed number of hours. Then, we asked respondents to make two choices related to V2G-EVs. In each of the choice exercises, we asked respondents to consider three vehicles: two V2G-EVs with different contract terms for buying back power and one GV. The GV was their "preferred gasoline vehicle" based on a 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 gasoline). The preferred GV and the amount of money the respondent planned to spend were mentioned in the preamble to the question, reminding the respondent what he or she had reported previously. Since we used the same response format and the same vehicle in the C-EV choice experiment, it should have been familiar to the respondent. The two V2G-EVs were described as V2G enabled electric versions of their preferred GV. Respondents were told that other than the characteristics listed, the V2G-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, color, look, safety, reliability, and so forth. The V2G-EVs were described by five C-EV attributes, three V2G contract terms, and price. To reduce the burden of comparing nine attributes across alternatives, we kept the five C-EV attributes fixed between the alternatives in the choice set in the V2G-EV experiment (see Figure 2). Since these five C-EV attributes were the same attributes used in the first choice, we already have information on how these are valued by respondents. By holding these attributes constant across alternatives in a choice set, we were able to focus respondents' attention on the contract terms and simplify the choice exercise.

The alternatives in the V2G –EV choice set then varied in price, required plug-in time per day (RPT), guaranteed minimum driving range (GMR), and annul cash back. Price was defined as the amount respondents would pay over the price of their preferred GV. RPT is defined as average daily plug-in time over the month, which gives drivers some flexibility in fulfilling the required number of hours per day by plugging in for more hours on days when their schedule allows and plugging in for fewer hours on days when it does not. GMR is defined as the minimum driving distance below which the power company would not draw down power. Respondents were told that the GMR will only occasionally be realized over a month (usually no power or only a modest amount of power would be drawn from a person's vehicle) and that they could always skip contract terms on days of heavy driving requirements so long as the monthly average was met.[2] Cash back was defined as the annual revenue a driver would earn from providing reserve service under the contract. Price was defined as the amount the respondent would pay above the price of the respondent's preferred GV. To cover the relevant range for each attribute, we used four levels for RPT and GMR, six levels for cash back and eight levels for price. The idea here is that the power companies or aggregators would set these requirements to establish the viable storage capacity of a fleet of vehicles. The larger the required the plug-in time and the lower the minimum guaranteed range, the larger the potential for capacity and hence the higher the cash back payment. Table 1 presents the attributes and their levels.

We used SAS's choice macro function to configure and generate our choice sets (Kuhfeld, 2005). The main challenge in developing the design is obtaining prior parameters. Researchers have used different sources to get priors including manager's prior beliefs (Sandor and Wedel, 2001) and estimates from a pilot pretest (Bliemer and Rose, 2011). We used data from our last pretest to estimate the prior parameters. A total of 243 respondents participated in the pretest, each answering two choice questions. This gave us 486 observations, which we used to estimate a simple multinomial logit model. The parameter estimates from this model were then used as the prior parameters in developing the final choice design. The final design for the V2G-EV choice experiment had 36 choice sets in 18 blocks and a D-efficiency of 6.0. The blocks were randomly assigned to respondents during the survey.

[2] While we informed respondents that the GMR will only occasionally be realized, in retrospective, it would have been better if we had informed them how often it will be realized exactly and perhaps even make this an attribute in the model.

We also included a correction for yea saying in our choice response format for about one-third of the sample (Blamey et al., 1999). We were concerned that respondents might report purchasing an EV as a way of showing favor for electric vehicles and perhaps even green energy policies in general when in fact they would not actually buy. The last response option shown in Figure 1 and 2 is our yea-say correction. That option essentially allowed people to say "I like the idea of V2G" (registering favor with concept) "but not at these prices" (showing their real likelihood of purchase). Although a large share of the sample chose the yea-say response in the V2G-EV experiment, there appeared to be little yea-saying bias in our survey. With the yea-saying treatment, the share of V2G-EV choices dropped by on 0.5%. Most of the votes for the yea-saying option, in other words, came from respondents who otherwise would have reported purchasing a GV.

IV. Econometric Model

Our model combines the C-EV choice data with the V2G-EV data and uses a structure much like that in HPKG (2011), where we only considered the C-EV choice data. Again, we use a latent class random utility model.

Our RUM model for an individual has the form

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

where $i = 1, 2$ for the two EVs in the choice set and $i = 0$ for the GV. Δp_i is the price difference for the EV versus GV. The vector $\boldsymbol{x}_i$ includes all of the conventional EV attributes: driving range, charging time, pollution reduction, performance, and fuel cost saving. The vector $\boldsymbol{y}_i$ includes the V2G contract terms from the second set of choice questions: minimum guaranteed driving range, required plug-in time, and cash back payments. The variable d is a dummy, where $d = 1$ if the choice pertains to a V2G-EV from the second pair of choice questions and $d = 0$ if the choice pertains to a C-EV from the first pair of choice questions. The errors terms ε_i and ε_0 are assumed to have type-1 extreme value distributions that give a multinomial logit probability of the form

$$(2) \qquad L(\beta) = \frac{\delta_1 \exp(\beta_p \Delta p_1 + \boldsymbol{\beta}_x \boldsymbol{x}_1 + \boldsymbol{\beta}_y \boldsymbol{y}_1 d)}{I} + \frac{\delta_2 \exp(\beta_p \Delta p_2 + \boldsymbol{\beta}_x \boldsymbol{x}_2 + \boldsymbol{\beta}_y \boldsymbol{y}_2 d)}{I} + \frac{\delta_0}{I}$$

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 chooses GV; $I = 1 + \sum_{i=1}^{2} \exp(\beta_p \Delta p_i + \boldsymbol{\beta}_x \boldsymbol{x}_i + \boldsymbol{\beta}_y \boldsymbol{y}_1 d)$; and $\boldsymbol{\beta} = (\boldsymbol{\beta}_p, \boldsymbol{\beta}_x, \boldsymbol{\beta}_y)$.

The latent class portion of the model, which captures preference heterogeneity, has the form

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

where the first term $\frac{\exp(\alpha^c z)}{\sum_{c'=1}^{C} \exp(\alpha^{c'} z)}$ is the probability of class membership and the second term $L(\beta^c)$ is the logit probability from equation (2) now defined for each class c. The term z is a vector of individual characteristics; C is the number of latent classes; $\beta = (\beta^1,...,\beta^C)$ so each class has its own set of random utility parameters; $\alpha = (\alpha^1,...,\alpha^C)$; and one vector α^c is set equal to zero for normalization so there are C sets of β_c and $C-1$ sets of α_c. Equation (3) enters the likelihood function for each respondent and each respondent has four entries – two for the C-EV questions and two for the V2G-EV questions.

V. Estimation Results

Testing for Scale Differences

We tested for scale difference in the C-EV and V2G-EV portions of the model. A scale difference, or what is the same a difference in error variances, may arise for a number of reasons – different attribute sets, different vehicle types, and different placement of questions in the survey. We used Hensher and Bradley's (1993) nested logit "trick" and found that the scale parameters in the two data sets are not statistically different. Given the near equivalence of the two sets of choice questions, this is not a surprising result. We constrain the scales to be the same thorough this paper.

Choosing Number of Preference Classes

We estimated our model with 2, 3, and 4 classes and then compared two measures of fit: Akakie Information Criterion (AIC) and Bayesian Information Criterion (BIC). The two-class model dominated – the same finding from our earlier paper. The 4-class model failed to converged. The 3-class model converged but included a class with less than one percent membership and with standard errors orders of magnitude larger that the parameter estimates. In the two-class model, one class was easily identified has EV-oriented and other GV-oriented.

Parameter Estimates Overlapping With HPKM (2011)

The parameter estimates from the class membership model (α^c) and parameters estimates on the basic EV attributes (β_x^c) are close to the results from HPKG (2011). Given our survey design, this was expected. For completeness we still present the estimates of α^c and β_x^c here, but our discussion will be abbreviated since the results are nearly the same as in our earlier paper.

The class membership model is shown in Table 3. The model normalizes the parameter vector to the GV-oriented class so the estimated parameters represent the partial contribution of each variable to the likelihood of being in the EV-oriented class. For example, the parameter on Gasoline Price is positive and significant indicating that people who expect gasoline prices to rise in the next five years are more likely to be in the EV-oriented class. The odds-ratio estimates of the coefficients are also shown in Table 3. This gives the relative odds of a person being in one class versus the other for a given change in an attribute. For example, the odds ratio of 3.0 on Hybird indicates that a person whose preferred GV is a hybrid is three times more likely to be EV-oriented than GV-oriented.

The class membership model, based on sign and significance of the parameters, indicates that the probability of purchasing an EV increases with youth and if you are male. It also increases for those who think gasoline prices will rise, have a green life style, have a hybrid car as a preferred GV, and have a residence that will accommodate an EV outlet for charging. People interested in new products and those who make more 'long drives' are also more likely to buy EV. The latter may be driven by a desire for greater possible fuel savings.

The parameter estimates for the basic EV attributes in the random utility model are shown in Table 4. The probability of purchasing an EV increases with driving range, reduced charging time, greater fuel savings, better performance, and less pollution. The table also shows the implicit prices for each attribute relative to the indicated baseline. For example, the willingness to pay for 300 miles of drive range versus the baseline 75 miles is $11,653. See HPKG 2011 for more. Now lets turn to the contribution of this paper – the analysis of the V2G-EV choice questions.

V2G Parameters

The parameter estimates pertaining to the V2G attributes (β_y^c) were estimated simultaneously with the parameters in Table 4 and are shown in Table 5. There are four attributes: price difference between a V2G-EV and the respondent's preferred GV, annual cash back under the V2G-EV contract, guaranteed minimum driving range under the contract (GMR), and required plug-in time per day under the contract (RPT). The levels used for each attribute are given in Table 1.

We specified price and cash back as continuous variables, and GMR and RPT as step-wise dummy variables. The latter specification was based on Wald and log-likelihood ratio tests, which indicate a non-linear effect for these two attributes. We used the most-favorable levels of GMR and RPT as excluded categories, so the parameter estimates for these attributes are expected to have negative signs. The price coefficient is constrained to be the same for the V2G-EV and C-EV choices.

First, comparing the results of the MNL and LC models shows the advantage of the LC over MNL Model. The LC Model provides a statistically better fit and reveals significant preference heterogeneity in the data.

Second, the V2G-EV constants show a clear split in the classes. The V2G-EV constant for the EV-oriented class is positive and significant indicating, all else constant, a proclivity to buy electric, while the V2G-EV constant for the GV-oriented class is negative and significant indicating the reverse. These coefficients define our two classes.

Third, the other parameter estimates work much as expected. Respondents dislike high RPT and low GMR -- utility decreases as required plug-in time increases and as the minimum guaranteed driving range decreases. Also, the coefficient on price difference is statistically significant and negative, and the coefficient on cash back is statistically significant and positive. The latter implies that the more revenue a person earns on a V2G vehicle the more likely he/she is to buy it. Again, all this is reasonable.

We also present implicit prices in Table 5. The implicit prices for each class are estimated by simply dividing the attribute coefficient by the coefficient estimate on price. The probability-weighted prices are estimated by weighting the implicit price for each person by his/her probability of class membership times the respective implicit prices – the sample mean is reported in the table. Comparing the implicit prices between the two classes of the LC model shows the preference heterogeneity in the population. For example, respondents in the two classes differ in how they value cash back. The EV-oriented class discounted cash back less than the GV-oriented class. Annual cash back of $1000 over the life of the car is worth around $2400 in present value for the EV-oriented and only $1760 for the GV-oriented. Both classes discount cash back heavily. This discounting could be due to a perceived uncertainty about the V2G technology or its value. Or, it may also be due to respondents' mistrust of power companies as some people indicated in our focus groups. The classes also differ in their values for GMR and RPT. The GV-oriented appear to be indifferent to changes in GMT and RPT at lower levels but more adverse at the extremes – such as when GMR is as low at 25 miles and RPT is a high as 20 hours/day.

The weighted implicit prices in Table 5 show that respondents see a high inconvenience with GMR and RPT over ranges actually being consider for policy. Reducing GMR from 175 to 125 is the equivalent to increasing the initial price of the car by $497. Not much. But, increasing it from 175 miles to 75 miles is equivalent to increasing the initial price by $4,020, and reducing it from 175 to 25 miles is equivalent to an $8,438 increase. Note that the implicit prices increase at an increasing rate: $10/mile (in the range 175 to 125 miles), $70/mile (125 to 75 miles) and $88/mile (75 to 25 miles). For comparison, the per-mile implicit prices for increased driving range in the C-EV model are $33/mile (in the range 300 to 200), $60/mile (150-200 miles), and $71/mile (75-150). There is reasonable correspondence between what these variables measure, so the preference consistency here looks good.

For RPT, the reference level is 5 hours per day - a rather short period of required plug-in time. On average, increasing RPT from 5 hours to 10 hours is equivalent to increasing initial price by $1,411. Increasing it further to 15 hours and 20 hours is equivalent to increasing initial price by $4,454 and $8,504. The per-hour incremental costs are $282/hour (5 to 10 hours), $608/hour (10 to 15 hours), and $810/hour (15 to 20 hours). Values from the C-EV model for charging time for the battery are estimated at $434/hour (in the range 5 to 10 hours), $945/hour (1 to 5 hours), and $3,331/hour (1 hour to 10 minutes). The correspondence of what these two variables measure is not as close as the correspondence of what the range variables measure, hence we should not expect similarity in values. Charging time over the basic set of attributes measures the speed with which a battery can be charged, while GMR measures a required plug-in time to satisfy a contract whether the battery is a fast-charging one or not. Also, the basic charging time measure is over much lower absolute charging time levels (egs., in ranges of 10 minutes to and hour and one hour to 5 hours). So, while the two measures are somewhat related, the comparison is a bit strained. The high performance of the battery appears to be more valuable, which makes sense if people recognize, and we assume they do, that most cars are idle for a large fraction of the day and that the contract allows for skipping required plug-in times on certain days provided the daily average is maintained over a month.

Still, we find the RPT coefficients surprisingly high given that the average car is idle about 23 hours/day. Although plug-in options may not be available away from home (we discussed at-work plug in options in the survey and assume respondents considered the likelihood of this for their own circumstance), the range of RPTs we used should not have been viewed as too constraining for most people if they keep their vehicle plugged in while at home. In any case, respondents did not appear to treat RPT as the simple use of idle vehicle time.

VI. Can the V2G concept help sell EVs?

In this section we use our model to judge whether or not the V2G concept can help EVs on the market. EVs are more costly than GVs and it is still uncertain whether battery technologies will improve enough or gasoline prices increase enough for EVs to make significant inroads in the market. Here is where V2G-EVs come into the picture. Since they provide some payment to owners in the form of cash back for energy returned to the grid, they can make EVs attractive to potential buyers. If the cash payments are large relative to the implicit inconvenience costs, then the net added value of V2G to an EV will be high and may help EVs on the market.

We used our model to see if this might be the case. First, we estimated the cash back required to compensate people for different combinations of the RPT and GMR (our measures of inconvenience) and compared it to estimated payments that may actually be feasible. If the required cash payments are low relative to what is feasible, there is potential for net added value to consumers for V2G and hence help for EVs on the market. Second, since cash back was heavily discounted in our model, we also considered up-front payment in the form of a reduced vehicle price to compensate for the V2G inconveniences. This should be a more effective way to increase the added value of V2G because people value up-front cash significantly more in our experiment.

The minimum cash back required to compensate a person for RPT and GMR inconvenience in our model is the value of $MCBC$ that solves the following equation

$$\begin{aligned} &\beta_p \Delta p + \boldsymbol{\beta}_x \boldsymbol{x} + \varepsilon_{EV} \\ &\quad = \beta_p \Delta p + \boldsymbol{\beta}_x \boldsymbol{x} + \beta_{CB} MCBC + \beta_{RPT} RPT + \beta_{GMR} GMR + \varepsilon_{V2G}, \end{aligned} \tag{4}$$

where the left-hand side is the utility for a C-EV, the right-hand side is the utility for a V2G-EV, and $\beta_{CB}MCBC + \beta_{RPT}RPT + \beta_{GMR}GMR = \boldsymbol{\beta}_y \boldsymbol{y}$ -- the individual contract terms in the vector $\boldsymbol{y}$. This measure simply seeks the cash back value that makes a person indifferent between a C-EV and a V2G-EV with contract terms RPT and GMR. Solving for $MCBC$ gives

$$(5) \qquad MCBC = \frac{\beta_{EV} - \beta_{V2G} - \beta_{RPT}RPT - \beta_{GMR}GMR + \varepsilon_{EV} - \varepsilon_{V2G}}{\beta_{CB}}$$

where $\beta_p \Delta p + \boldsymbol{\beta}_x \boldsymbol{x}$ cancels after we pull the EV and V2G constants (β_{EV}, β_{V2G}) from the $\boldsymbol{x}$ vector on both sides.[3] Since each respondent has some predicted probability of being in each of the two classes, we use the following weighted measure of minimum cash back compensation in our computations

$$(6) \qquad MCBC_w = P_{EV} MCBC_{EV} + (1 - P_{EV}) MCBC_{GV}$$

where P_{EV} is the probability of membership in the EV-oriented class, $1 - P_{EV}$ is the probability of membership in the GV-oriented class, and $MCBC_{EV}$ and $MCBC_{GV}$ are conditional minimum compensation requirements for each class. This approach follows Boxall and Adamowicz (2002).

The same calculation for minimum up-front price reduction is the value of MPR that solves

[3] The C-EV constant here is adjusted to correspond to the C-EV attribute levels shown at the bottom of Table 1. This makes them consistent with the EV configuration held fixed in the V2G experiment.

$$(7) \quad \begin{aligned} &\beta_p \Delta p + \boldsymbol{\beta}_x \boldsymbol{x} + \varepsilon_{EV} \\ &\qquad = \beta_p(\Delta p - MPR) + \boldsymbol{\beta}_x \boldsymbol{x} + \beta_{CB} 0 + \beta_{RPT} RPT + \beta_{GMR} GMR + \varepsilon_{V2G} \end{aligned}.$$

In this case the compensatory value is implicitly and asset value in present value terms. A weighted measure, MPR_w, is derived in the same way as $MCBC_w$ is derived.

Our calculation of $MCBC_w$ for several V2G scenarios is shown in Table 6. The contracts were constructed using RPT (= 5, 10, 15 and 20 hours) and GMR(= 25 and 75 miles). We decided not to use higher GMRs because we wanted to stay within the driving range of current and near-term EVs and most have less than 150 miles driving range.

The estimated minimum required compensation for each contract is shown using a Box-Whisker Plot in Figure 3 – the dispersion comes from enumeration over the sample since each respondent has a different EV and GV orientation weight. These estimated $MCBC_w$'s are annual minimum required contract prices over the sample. The median required compensation ranges from a low of near \$2,368 for Contract A (GMR= 75 & RPT=5) to a high of near \$8,622 for contract H (GMR= 25 & RPT=20). The question then is whether or not these amounts, especially those at the minimums in Figure 3 for each scenario, since this is where the signing is mostly to take place, are feasible in the market.

The actual revenue a V2G-EV can earn depends on many factors including the type of power market (spinning power versus regulation power), the region of the country, power capacity of the connection, hours connected, and so forth. We used a study by Kempton and Tomic (2005) to assess the feasibility of attaining our estimated earnings requirements. Kempton and Tomic (2005) estimated the potential net revenue a Toyota RAV4 EV can earn with RPT = 18 and GMR = 20. They calculated revenue net of depreciation and other equipment costs associated with providing reserve service. Their contract is on the high-inconvenience side of our contract scenarios - something like Contract H. Using real world power market data from a 2003 California Independent System Operators (CISO) power market, they found, under the best scenario (providing regulation service), that a Toyota RAV4 EV could earn net revenue of $2,554 annually (close to $2900 in 2009$). Our Figure 3 shows that the minimum required contract payments for a similarly configured contract (GMR= 25 & RPT=20) are near $8,000. Making roughly the same calculations for the other scenarios has little affect on the story. Hence, if the Kempton and Tomic (2005) assumptions hold, it would appear that V2G is not likely to help EVs on the market if contracts such as those described in our survey are used. There are, of course, a number of things that could alter this result. Technology is changing fast and may lower the cost at which aggregators or power companies can withdraw energy. And, the cost of energy from conventional sources could rise making the storage of power more valuable. Still the gap to close is large.

A more promising approach for payment would appear to be up-front price discounts on V2G vehicles since respondents were shown to discount cash-back payments heavily. Figure 4 shows the same Box-Whisker Plot for an up-front cash discount. These are calculated using equation (7). The up-front discount for Contract H in this case is near $14,000 for those requiring the minimum compensation. Annualized these over 8 years (as an example contract length and using a 5% discount rate for the power company's money), gives $2,190. This appears to be low enough to bring some into the market, since we estimate that aggregators could pay about $2900/year. Still the V2G value does not overwhelm the compensation required.

Another strategy that aggregators may consider is a pay-as-you-go contract. These contracts would have no required plug-in times. Instead, power companies would simply pay owners for power capacity on an hour-by-hour basis, which could vary with power prices over time. There would still be the issue of people waking up to a vehicle with a much-depleted battery, but consumers would be free to plan against such inevitabilities and a GMR could still be used. One difficulty with this approach is the uncertainty is poses to aggregators – at any point in time an aggregator cannot be sure how much back-up power it has. Indeed, the main reason for the contracts is for aggregators to have greater certainty about its level of back-up power. Presumably, in time, using historic data on patterns of usage, aggregators would learn about capacity fluctuations (percent of the V2G vehicles plugged-in) from a given fleet size and could plan according. No doubt the size of the required fleet would be larger than under the contract terms approach. There is also the possibility of a hybrid approach where some customers sign contracts and other use pay-as-you-go.

VII. Conclusion

We found that drivers see high inconvenience cost with signing V2G-EV contracts. This is probably due to a combination of many factors, including drivers' desire for flexibility in car use, their lack of awareness of how many hours their cars are parked, and their concerns that they may not know how to opt out of some contract terms. We also found drivers discount revenue from V2G-EV contracts heavily. This is probably due to driver's uncertainty about earning money from re-selling power back to power companies. The combined effect of the two factors is that drivers demand a high price to sign V2G contracts, which will reduce the competitiveness of V2G-EV power in the power market.

We suggested two strategies as alternatives to the strict cash-back-contract approach, which has gotten most of the attention to date. One strategy is to eliminate contract requirements completely and allow consumers to provide the service at their convenience on a pay-as-you-go basis. This eliminates some of the inconvenience cost of signing V2G-EV contracts and makes V2G-EVs more attractive to consumers. Another strategy is for power aggregators to consider providing consumers with cash payment in advance in exchange for signing a V2G-EV contract. This approach eliminates the uncertainty associated with earnings from V2G power and reduces the high discount rate consumers seem to apply for revenue from V2G-EV contracts. While more research is required, both strategies seem like feasible avenues for the V2G technology.

On the methodological front, our analysis also offered an approach for conveying complex commodities to survey respondents. We did this by dividing the experiment into two separated but logically connected smaller experiments – one for a conventional EV and then a second for a vehicle-to-grid EV. In this way we were able bring respondents along slowly as the learned the material and forced them to evaluate their options stepwise in the two simpler experiments. In focus groups, we found that the stepwise approach improved comprehension. In pretests, we found that it improved the sharpness of our parameter estimates.

Table 1: Attributes and Levels Used in the V2G Choice Experiment

Attributes	**Levels**
Minimum guaranteed driving range (GMR)	25 miles 75 miles 125 miles 175 miles
Required plug-in time per day (RPT)	5 hours 10 hours 15 hours 20 hours
Annual cash back payment (CB)	\$500 \$1,000 \$2,000, \$3,000 \$4,000 \$5,000
Price relative to your preferred GV (ΔP)	Same \$1,000 higher \$2,000 higher, \$3,000 higher \$4,000 higher, \$8,000 higher \$16,000 higher \$24,000 higher

The following attributes were held constant in the experiment:

Driving range on full battery	200 miles
Time it takes to charge battery for 50 miles of driving range	1 hour
Acceleration relative to your preferred GV	5% faster
Pollution relative to your preferred GV	75% lower
Fuel cost	Like \$1.00/gal gas

Table 2: Definition and Descriptive Statistics for Variables Used in LC Model (n = 3029)

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)
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	

Table 3: Class Membership Model (GV-oriented is the excluded class)

Variables	Coefficient	T-Stat.	Odds Ratio
Class membership constant	-2.9	-11.8	0.06
Young [1]	0.72	5.6	2.1
Middle age[1]	0.22	1.96	1.2
Male	0.32	3.4	1.4
College	0.13	1.3	1.1
Income (000$)	-0.0023	-1.9	0.99
Gasoline price ($/gallon)	0.06	2.4	1.1
Hybrid	1.1	10.2	3.0
Outlet	1.1	9.9	3.0
Multicar	-0.04	-0.4	0.96
Small car[2]	0.2	1.5	1.2
Medium car[2]	0.15	1.5	1.2
Long drive	0.29	3.0	1.3
Major green[3]	1.1	7.6	3.0
Minor green[3]	0.68	5.4	2.0
New goods	0.51	5.6	1.7
Log likelihood value	-9472.1		
Sample size	12116		

See Table 2 for variable definitions.

1. Excluded category is Old (>56)
2. Exclude category is Large Car.
3. Excluded category is Not Green.

Table 4: Parameter Estimates and Implicit Prices for the C-EV Portion of the Latent Class RUM Model

	Parameters		Implicit Prices	
	GV-Oriented Class	**EV-Oriented Class**	**Weighted Average**	**Per Unit**
EV Constant	-4.05	0.45		
	(-9.9)	(2.5)		
Yea Saying Tendency	-0.11	-0.28		
	(-0.93)	(-2.9)		
Price (in 000)	-0.167	-0.078		
	(-11.1)	(-27.1)		
Fuel Cost	-0.15	-0.33	-$2,776	
	(-1.3)	(-6.3)		
Driving Range on full battery (excluded category is 75 miles)				
150 miles	0.83	0.44	$5,322	$71
	(3.9)	(5.0)		
200 miles	0.89	0.84	$8,333	$60
	(4.2)	(10.0)		
300 miles	1.3	1.14	$11,653	$33
	(6.3)	(11.8)		
Charging time for 50 miles of driving range (excluded category is 10 hours)				
5h	0.58	0.09	$2,194	$434
	(2.7)	(1.2)		
1h	1.05	0.45	$5,972	$945
	(5.3)	(5.7)		
10min	1.31	0.74	$8,748	$3,331
	(6.7)	(9.4)		
Pollution Relative to preferred GV (excluded category is 25% lower)				
50% lower	0.15	0.05	$726	$29
	(0.68)	(0.5)		
75% lower	0.36	0.07	$1,455	$29.2
	(2.0)	(0.8)		
95% lower	0.54	0.28	$3,466	$101
	(2.8)	(3.2)		
Acceleration relative to preferred GV (excluded category is 20% slower)				
5% slower	0.58	0.06	$1,932	$129
	(2.7)	(0.7)		
5% faster	0.91	0.28	$4,452	$252
	(4.1)	(3.2)		
20% faster	1.2	0.50	$6,631	$145
	(5.3)	(5.6)		
Log likelihood	-9459.72495			
Sample size	12116			

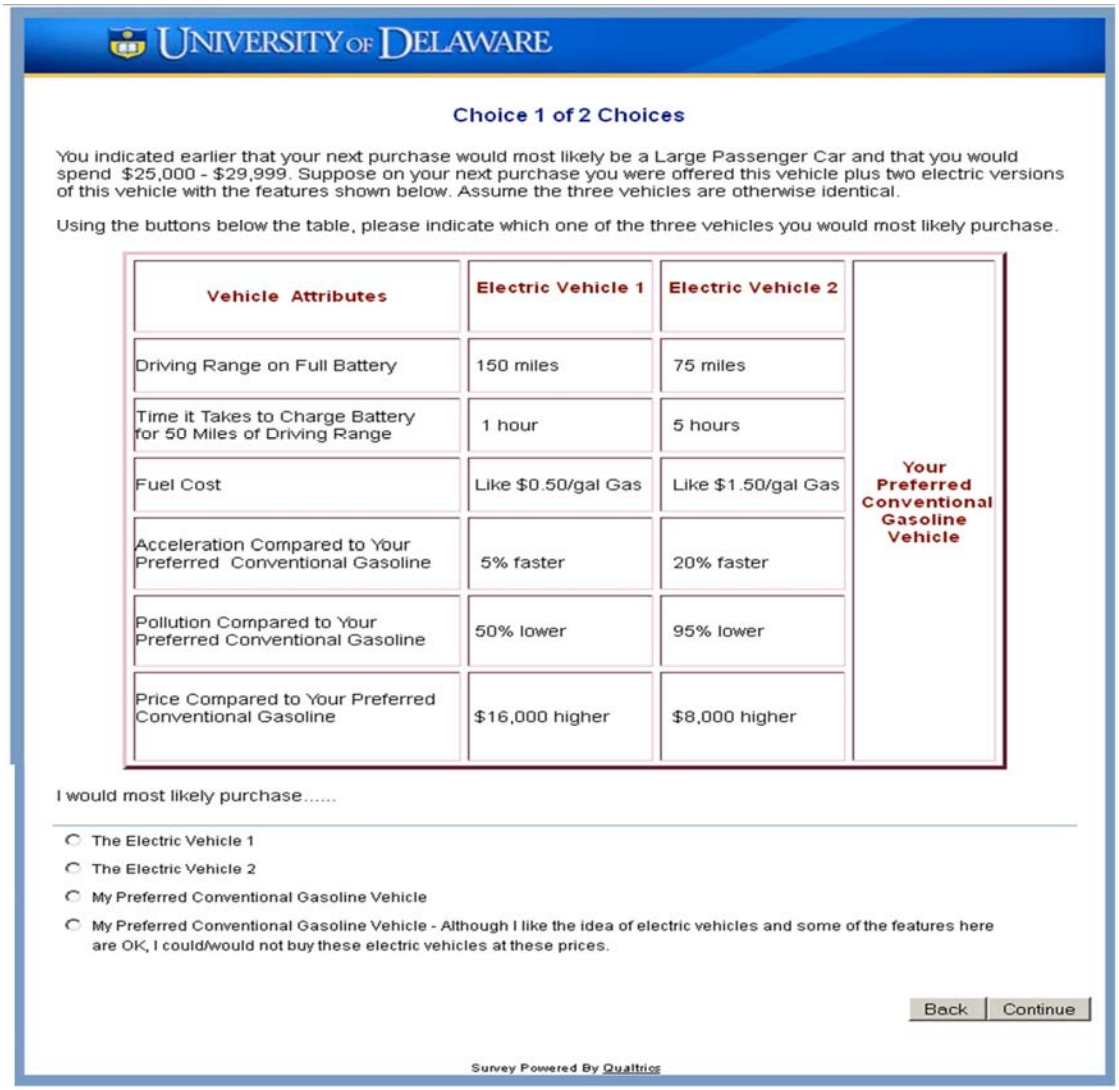
Table 5: Parameter Estimates and Implicit Prices for the V2G-EV Portion of the Latent Class RUM Model (t-statistics in parenthesis)

Attributes	MNL Model	Latent Class Model		Implicit Prices for Latent Class Model		
		GV-Oriented Class	EV-Oriented Class	GV-Oriented Class	EV-Oriented Class	Weighted Average
V2G constant	-1.1	-2.07	2.5			
	(-8.0)	(-2.1)	(18.1)			
Yea saying tendency	-0.22	-0.11	-0.28			
	(-5.2)	(-0.81)	(-2.8)			
Price relative to preferred GV (000)	-0.08	-0.17	-0.08			
	(-26.9)	(-11.0)	(-27.2)			
Cash Back (000)	0.16	0.30	0.19	$1.76	$2.4	$2.1
	(11.0)	(6.6)	(10.3)			
GMR = Guaranteed Minimum Driving Range (excluded category is 175 miles):						
125 miles	-0.05	0.26	-0.17	$1,529[1]	-$2,125	-$497[1]
	(-0.9)	(1.4)	(-2.35)			
75 miles	-0.29	-0.37	-0.44	-$2,176[1]	-$5,500	-$4,020
	(-5.1)	(-1.91)	(-6.03)			
25 miles	-0.66	-1.13	-0.79	-$6.647	-$9,875	-$8,438
	(-9.0)	(-3.8)	(-9.3)			
RPT=Length of Required Plug-In Time Per Day (excluded category is 5 hours):						
10 hours	-0.11	0.07	-0.23	$412[1]	-$2,875	-$1,411[1]
	(-2.0)	(0.36)	(-3.1)			
15 hours	-0.32	-0.43	-0.48	-$2,529	-$6,000	-$4,454
	(-5.7)	(-2.1)	(-6.3)			
20 hours	-0.63	-1.42	-0.69	-$8,353	-$8,625	-$8,504
	(-9.8)	(-5.5)	(-8.9)			
Log likelihood value	-10938.8	-9472				
Sample size	12064	12116				

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

Table 6: Contract Configurations and Required Compensation Under Cash-Back and Up-Front Payment

Contract Term Scenario	GMR	RPT	Median Required Annual Cash-Back	Median Required Up-Front Payment
A	75 miles	5 hours	$2,368	$4,252
B	75 miles	10 hours	$3,052	$5,875
C	75 miles	15 hours	$4,419	$8,741
D	75 miles	20 hours	$6,480	$12,758
E	25 miles	5 hours	$4,511	$8,668
F	25 miles	10 hours	$5,195	$10,292
G	25 miles	15 hours	$6,562	$13,157
H	25 miles	20 hours	$8,622	$16,628



UNIVERSITY OF DELAWARE

Choice 1 of 2 Choices

You indicated earlier that your next purchase would most likely be a Large Passenger Car 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	150 miles	75 miles	
Time it Takes to Charge Battery for 50 Miles of Driving Range	1 hour	5 hours	
Fuel Cost	Like $0.50/gal Gas	Like $1.50/gal Gas	
Acceleration Compared to Your Preferred Conventional Gasoline	5% faster	20% faster	
Pollution Compared to Your Preferred Conventional Gasoline	50% lower	95% lower	
Price Compared to Your Preferred Conventional Gasoline	$16,000 higher	$8,000 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

Figure 1: Sample C-EV Choice Question

UNIVERSITY OF DELAWARE

Choice 2 of 2 Choices

Now, consider a different set of vehicles. Using the buttons below the table, please indicate which one of the three vehicles you would most likely purchase.

Vehicle Attributes	V2G Electric Vehicle 1	V2G Electric Vehicle 2	Your Preferred Conventional Gasoline Vehicle
Driving Range on Full Battery	200 miles	200 miles	
Time it Takes to Charge Battery for 50 Miles of Driving Range	1 hour	1 hour	
Acceleration Compared to Your Preferred Conventional Gasoline	5% faster	5% faster	
Pollution Compared to Your Preferred Conventional Gasoline	75% lower	75% lower	
Fuel Cost	Like $1.00/gal Gas	Like $1.00/gal Gas	
Guaranteed Minimum Driving Range on V2G Contract	125 miles	25 miles	
Average Length of Required Plug in Time Per Day with Energy Dial Set to 'Sell' on V2G Contract	20 hours	15 hours	
Cash Payment Made to You on V2G Contract	$2,000/year	$3,000/year	
Price Compared to Your Preferred Conventional Gasoline	$1,000 higher	$24,000 higher	

I would most likely purchase.....

- The V2G Electric Vehicle 1
- The V2G 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 2: Sample V2G-EV Choice Question

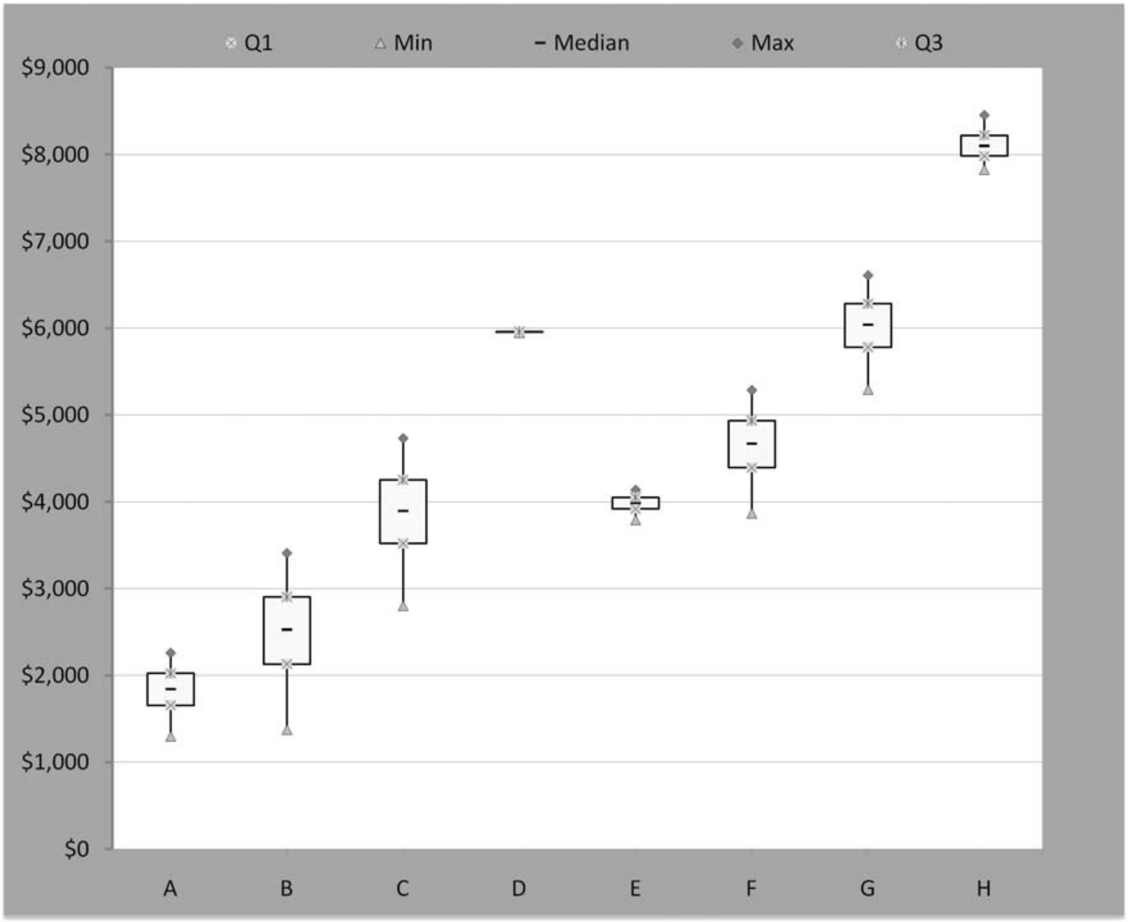


Figure 3: Box-Whisker Plot Based for Minimum Required Annual Compensation in Cash-Back Terms for eight contracts (A through H) listed in Table 6. The range of required compensation payments is due to the variation (heterogeneity) over the sample.

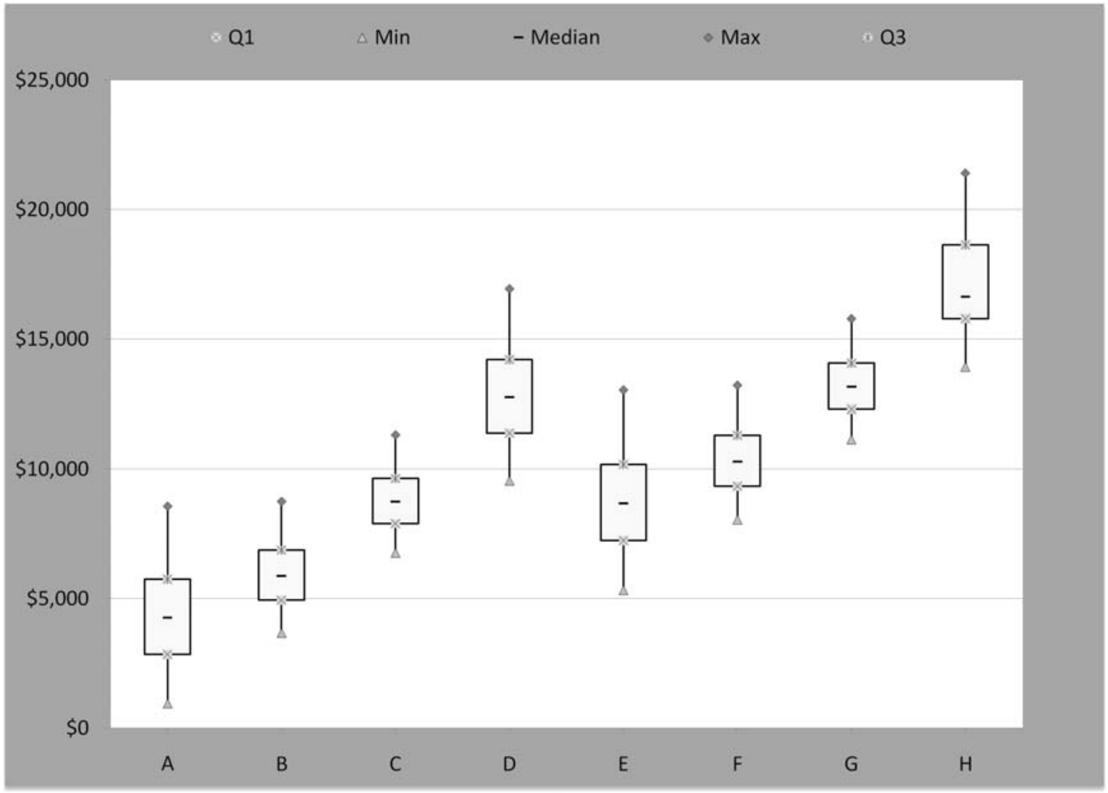


Figure 4: Box-Whisker Plot for Upfront Discounts on Purchase of Vehcile for eight contracts (A through H) listed in Table 6. The range of required compensation payments is due to the variation (heterogeneity) over the sample.

References

Blarney, R.K., J. W. Bennett, and M. D. Morrison. 1999. Yea-Saying in Contingent Valuation Surveys. *Land Economics*, 75 (1): 126-141.

Bliemer, Michiel C.J. and John M. Rose. 2011**.** Experimental Design Influences on Stated Choice Outputs: An Empirical Study in Air Travel Choice. *Transportation Research Part A*, 45: 63-79.

Boxall, Peter C., and Wiktor L. Adamowicz. 2002. Understanding Heterogeneous Preferences in Random Utility Models: A Latent Class Approach. *Environmental and Resource Economics,* 23(4): 421-446.

Greene, William H., and David A. Hensher. 2003. A Latent Class Model for Discrete Choice Analysis: Contrasts with Mixed Logit Model. *Transport research part B: Methodological*, 37(8): 681-98.

Hidrue, Michael K., George R. Parsons, Willett Kempton, and Meryl P. Gardner. 2011. Willingness to Pay for Electric Vehicles and Their Attributes. *Resource and Energy Economics*, 33(3):686-705.

Kempton, Willett and Amardeep Dhanju. 2006. Electric Vehicles with V2G: Storage for Large-Scale Wind Power. *Windtech International*, 2 (2): 18-21.

Kempton, Tomic, Letendre, Brooks & Lipman. 2001. Vehicle-to-Grid Power: Battery, Hybrid, and Fuel Cell Vehicles as Resources for Distributed Electric Power in California. Report UCD-ITS-RR-01-03, UC Davis.

Kempton, Willett and Josna Tomić. 2005. Vehicle to Grid Fundamentals: Calculating Capacity and Net Revenue." *Journal of Power Sources,* 144 (1): 268-279.

Kuhfeld, Warren F. 2005. Marketing Research Methods in SAS: Experimental Design, Choice, Conjoint, and Graphic Techniques. SAS 9.1 Edition TS-722.

Sandor, Zsolt and Michael Wedel. 2001. Designing Conjoint Choice Experiments Using Manager's Prior Beliefs. Journal of Marketing Research, 38:430-444.

Shonkwiler, Schott J., and Douglass W. Shaw. 2003. A Finite Mixture Approach to Analyzing Income Effects in Random Utility Models: Reservoir Recreation along the Colombia River. In *The New Economics of Outdoor Recreation*, ed. Nick D. Hanley, Douglass W. Shaw, and Robert E. Wright, 268-278. Northampton: Edward Elgar.

Swait, Joffre. 2007. Advanced Choice Models. In *Valuing Environmental Amenities Using Stated Choice Studies*, ed. Barbara J. Kanninen, 229-29. Dordrecht: Springer.

Swait, Joffre. 1994. "A Structural Equation Model of Latent Segmentation and Product Choice for Cross-Sectional Revealed Preference Choice Data." *Journal of Retailing and Consumer Service*, 1(2): 77-89.