Can Vehicle-to-Grid Revenues Improve Market for Electric Vehicles?

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Abstract

Vehicles with vehicle-to-grid (V2G) power and grid-integrated vehicle (GIV) controls have power electronics that can return stored power back to the power grid at times of greatest value. Since providing this service can provide payments to vehicle owners in some jurisdictions, it could be an additional value stream to reduce the cost of ownership of electric vehicles. Using data from a national stated preference survey, this paper presents the first study of consumer demand for V2G enabled electric vehicles. In our choice experiment, 3029 respondents compared their preferred gasoline vehicle with two V2G-equivalent vehicles. The V2G vehicles were described by a set of electric vehicle attributes and a set of contract requirements for V2G payments, such as "required plug-in time", and "guaranteed minimum mileage". The contract requirements specify a contract between drivers and the power aggregator for providing reserve power to the grid. We found drivers associate high inconvenience cost with such contracts, and interpreted terms like "required plug-in time" as restrictive on their driving. These effects lowered the competitiveness of V2G vehicle power. Our findings suggest that for the V2G concept to help EVs in the market, V2G contracts should be completely eliminated.

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

I. Introduction

Vehicle-to-grid power (V2G) is a new concept in electric vehicle design[1]. 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 (GIV) with V2G additionally has controls so that the vehicle will charge and discharge at the economically valuable times. The idea behind such a design is to use parked EVs as a source of reserve power to the electric grid. The electric grid needs reserve power to smooth fluctuation in their generation, and respond to unexpected equipment failures. This is now done with large generators, but can be done more economically with EVs, using the idle capacity in their batteries. The average US car is parked 95% of the time (Pearre 2011). With a proper technology, EVs may be able to provide reserve service at a much lower cost and pay the owners of EVs for the service (Kempton and Tomic 2005).

Designing EVs with V2G capability has two advantages. (We here use "V2G" as shorthand for "electric vehicles with V2G power and GIV controls".) First, payment to owners of EVs may help lower the overall cost of ownership of EVs, which are currently above market price of gasoline vehicles. Kempton and Tonic (2005), for example, show a Toyota RAV4 EV can earn up to $2,554 annually from providing reserve service to the electric grid. Second, designing EVs with V2G capability enhances the environmental and energy security benefits of EVs. V2G vehicles can replace generators currently providing reserve service. Depending on the type of fuel used by the generators, this will have net environmental benefits. V2G vehicles can also support renewable sources of energy such as wind and solar (Kempton and Dhanju,

[1] The concept of using EVs for reverse power flow to the grid was first proposed by Kempton and Letendre (1997), the term "vehicle to grid" was first used in Kempton et al (2001), and a full treatment of the electrical engineering and economic equations first presented in Kempton and Tomic (2005).

2006). These renewable sources have fluctuating output and EVs can serve as a storage medium: charging during high production periods and discharging during low production periods.

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 from their car's batteries to power companies? If so, at what price? Can revenue earned from such a plan help EVs in 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 EVs (EVs with no V2G capability) and a choice experiment for V2G vehicles (EVs with V2G capability). We used data from the conventional EV choice to estimate consumers' willingness to pay for EVs and their attributes in our earlier paper (Hidrue et al., 2011). The current paper is a follow up and deals with the V2G vehicle choice data. In particular, we address two issues related to V2G vehicle choice. First, we estimate a vehicle choice model for V2G-capable vehicles, and estimate tradeoffs between different V2G contract term attributes. Second, we use parameter estimates from the model to simulate the value of different contract scenarios and evaluate whether designing EVs with a V2G capability will make them more attractive to consumers.

We used a latent class random utility model to analyze respondents' choice of V2G vehicles. This model assigns individuals into different preference classes and estimates a separate set of parameters for each class. The model allowed us to capture preference heterogeneity in the data. Our analysis indicates that consumer preference for V2G vehicles can be captured in two classes, which we labeled as EV-oriented consumers and GV-oriented (gasoline vehicle) consumers. Respondents in the EV-oriented class have higher proclivity toward V2G vehicles. The likelihood of a person being in the EV-oriented class increases if the person is young, male, has a plan to buy hybrid cars, has a place to install outlet for EVs at home, expects gasoline prices to increase in the next 5 years, frequently drives long distances, has a green life style, and has a tendency to buy new products.

We found significant differences in how respondents in the two classes value V2G vehicles, V2G contracts, and revenue from V2G contracts. Respondents in the EV-oriented class require less compensation to switch from a gasoline vehicle to a comparable V2G vehicle, and have lower discount rate on revenue from V2G contracts than do respondents in the GV-oriented class.

To assess the impact of designing EVs with V2G capability, we simulated several contracts and estimated the price respondents would ask for these contracts. The contracts included a requirement to keep the vehicle plugged in and available a minimum number of hours, and also insured that, despite V2G, a minimum battery range would always be available. We found respondents associate high inconvenience cost with contracts, which reduces or eliminates the additional value that V2G power was expected to add to the vehicle. 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, V2G contracts should not be used, or should not use strict terms.

II. The Concept of Vehicle to Grid

Vehicle to grid (V2G) power refers to the flow of power from electric vehicles back to the power grid. Here we call EVs with such capability V2G vehicles. These 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 (Pearre 2011). Typically, most of this time no charging is required, so the vehicle 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) but not yet traded on markets. Currently, these reserve services are supplied by large generators set to fluctuate in output, an operating mode that is inefficient and increases wear and maintenance costs. EVs can provide these reserves at a lower cost and the revenue earned from providing these electric services have been proposed as a possible revenue stream to help offset the currently-high cost of electric vehicles (Kempton and Letendre 1997; Kempton and Tomic 2005).

The amount of revenue a V2G vehicle can earn depends on many factors including the length of time the vehicle is plugged in and available to provide reserve service, size of the vehicle's battery, power of the charger, the vehicle's daily drive, and the type of reserve market. Generally, the value of the electric service is greater as: 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 vehicle are the ancillary services markets (A/S), called spinning reserves and regulation (Kempton and Tomic, 2005). 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 damp 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 reserve has to be available 24 hours a day, 7 days a week.

Spinning reserve and regulation are paid by capacity (kW); the energy payment is both for the time and amount used. This means, a V2G vehicle 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, after Kempton and Tomic (2005) called here an "aggregator", 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 car owners.

The relationship between the aggregator and the V2G car 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 car available for providing reserve service for a specified number of hours per day or month. In the latter, drivers would not have any obligation to provide reserve service. They would be paid for the number of hours their vehicle plugged in to provide the service. The advantage of a contract is that it provides more assurance of power capacity and revenue to the aggregator, and consequently also makes it possible for the aggregator to make up-front payments or investments in the customer's facilities. In this study, we followed a business model assuming a contract, similar to that discussed in Kempton and Tomic (2005) where V2G vehicle owners sign a contract with a power aggregator.

III. Survey Design

We designed a web-based national stated preference survey, conducted in 2009, to study consumer preference for conventional and V2G enabled electric vehicles. The survey has 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. Details about design of the survey, sample selection and characteristics of the data can be found in Hidrue et al (2011), which analyzes EV characteristics and their value to car buyers. Here, we focus on the part of the survey that relates to V2G vehicles.

The V2G section of the survey started with a description of the V2G concept. Respondents were told how a V2G vehicle works, how V2G contracts work, and how it may affect their driving behavior. Then, we asked respondents to make two choices related to V2G vehicles. In each of the two choice exercises, we asked respondents to consider three vehicles: two V2G vehicles 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). A sample question is shown in Figure 1. 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. The two V2G vehicles were described as V2G enabled electric versions of their preferred

GV. Respondents were told that other than the characteristics listed, the V2G vehicles 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 vehicles were described by five EV attributes, three V2G contract term attributes and price. To reduce the burden of comparing nine attributes across alternatives, we kept the five EV attributes fixed between the alternatives in the choice set. Since these five EV attributes were the same attributes used in the conventional EV choice, we already have information on how respondents value them. By holding these attributes constant, we were able to focus respondents' attention on the contract terms and simplify the choice exercise.

The design of the choice experiment varied price, average required plug in time per day (RPT), guaranteed minimum driving range (GMR), and annuls cash back. Price was defined as the amount respondents would pay over the price of their preferred GV. RPT was 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 for more hours when their schedule allowed for it and plugging in for fewer hours when it does not. GMR was defined as the minimum driving distance below which the power company would not draw down power. Cash back was defined as annual revenue a driver would earn from providing reserve service under the contract. 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. Table 1 presents the attributes and their levels.

We used SAS's choice macro function (Kuhfeld, 2005) to generate the choice sets. Given a prior parameter vector β, the algorithm for this macro searches for a design that minimizes the variance of the estimated parameters. One challenge in developing the design is getting the prior parameters before the data is actually collected. Researchers have used different sources to get the priors including manager's prior beliefs (Sandor and Wedel, 2001) and estimates from a pilot pretest (Huber and Zwerina, 1996; Bliemer and Rose, 2011). In our case, 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 that 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 had 36 choice sets in 18 blocks and a D-efficiency of 6.0. 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 a V2G vehicle option to register their support for the V2G concept even though they would not actually purchase a V2G vehicle at the cost and configuration offered. The yea-say option 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). 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 2 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 52 - 48 split between V2G vehicle and GV. Also, there appears to be very little yea-saying. That is, even with the additional response option, the selection of V2G vehicles dropped by only 0.5%. Similarly, in our conventional EV study, there was no significant yea-saying.

IV. Econometric Model

We estimated a latent class (LC) random utility model (Swait, 1994).[2] The LC model assigns individuals to classes by preferences and estimates a separate set of random-utility parameters for each class. Membership into the preference classes and the number of preference classes is unknown or 'latent'. The full model then has two sub models: a class membership model and a conditional random utility choice model.

The class membership model predicts the likelihood of belonging to a particular preference class as a function of individual specific characteristics and/or attitudinal constructs. Following Swait (1994), the probability an individual n belongs to class S can be specified as a multinomial logit model.

$$Q_{ns} = \frac{\exp(\theta_s Z_n)}{\sum_{s=1}^{S} \exp(\theta_s Z_n)}, \text{ S=1,…, S} \qquad (1)$$

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[2] We also estimated a multinomial logit model and mixed logit model. Comparison of the models on the basis of non-nested test statistics (Swait and Ben-Akiva, 1986), and within sample prediction showed the latent class model is superior to the other two models.

Where S is number of preference classes in the population, Z_n is a vector of individual specific attributes, and θ_s is a vector of class specific parameters corresponding to Z_n. For identification purposes, one vector of θ_s is normalized to zero. The variables that enter the vector Z_n and their definition are given in Table 4.

Given class membership, the conditional random utility choice model estimates the probability of choosing one of the three vehicles offered in our choice set. The utility individual n in class S gets from choosing one of these alternatives is a function of the choice attributes and can be specified as follows:

$$V_{nj|s} = \beta_s X_{nj} + \phi_s \Delta P_{nj} + \varepsilon_{nj|s} \tag{2}$$

Where X_{nj} is a vector of contract term attributes and ΔP_{nj} is price difference between the V2G vehicle and the respondent's preferred GV. The parameters β_s and ϕ_s are class specific parameters, and $\varepsilon_{nj|s}$ is an error term. Under the usual assumption of independent and identically distributed (iid) extreme value errors in (2), the conditional random utility choice model is given by the following standard logit model:

$$\pi_{(nj|s)} = \frac{\exp(\beta_s X_{nj} + \phi_s \Delta P_{nj})}{\sum_{j=1}^{J} \exp(\beta_s X_{nj} + \phi_s \Delta P_{nj})} \tag{3}$$

Equation (3) estimates the probability individual n chooses alternative j, conditional on the information that individual n belongs to class S. However, class membership is unknown. The unconditional probability, the probability that a random respondent in our sample chooses alternative k, is a joint probability of the class membership and the conditional choice probabilities.

$$\pi_{nj} = \sum_{s=1}^{S} \left(\frac{\exp(\theta_s Z_n)}{\sum_{s=1}^{S} \exp(\theta_s Z_n)} \right) \left(\frac{\exp(\beta_s X_{nj} + \phi_s \Delta P_{nj})}{\sum_{j=1}^{J} \exp(\beta_s X_{nj} + \phi_s \Delta P_{nj})} \right) \tag{4}$$

Where the first expression on the parenthesis is the class membership probability and the second expression is the conditional choice probability. For a given S, equation (4) is estimated using maximum likelihood procedures. The procedure estimates S vectors of β_s and $\phi_{s,}$ and S-1 vectors of θ_s.

As indicated earlier, the LC model allows for preference heterogeneity by estimating separate preference parameter for each class. Shonkwiler and Shaw (2003) and Swait (2007) also show the LC model is not constrained by the IIA property of the MNL model. However, as Greene and Hensher (2003) pointed out, the LC model does not capture correlation among multiple choices made by the same individual and this is the weakness of the model.

Finally, the above discussion assumed a given number of preference classes in the population. However, number of preference classes is also unknown and there is no rigorous model for selecting number of classes. The conventional approach in the literature is to use multiple information criteria coupled with the analyst's judgment. In our case, we used the Akakie Information Criterion (AIC), the consistent AIC (CAIC), and the Bayesian Information Criterion (BIC). The formulas for calculating each measure is given below:

$$\begin{aligned} AIC &= -2LL(\beta) + 2K \\ CAI &= -2LL(\beta) + K(\ln(N) + 1) \\ BIC &= -2LL(\beta) + K\ln(N) \end{aligned} \tag{5}$$

Where LL (B) is log likelihood value at convergence, K is the total number of parameters estimated, and N is sample size. The class size that minimizes each index is considered as the model with the best fit. However, the different criteria may not always select the same number of classes or the parameter estimates for the selected class size may have lower quality than an alternative class size. In all cases, the researcher's judgment is essential in selecting the optimal class size (Swait, 2007).

V. Estimation Results

Selecting Number of Preference Classes

We estimated models with 2, 3 and 4 classes. For each class, we calculated the AIC, the CAIC and the BIC. The resulting information is given in Table 5. The AIC suggested a four class model while the CAIC and BIC suggested a two class model. Further examination of the estimated parameters showed the two class model provides better fit to our data. For the 3 and 4 class models, the additional classes are very small (less than 1% of the sample each) and most of their parameters have large standard errors. Interpretation of the two class model is also more intuitive. This model predicted 44% of the sample is in the first class and the remaining 56% is in the second class.

Examining the parameters of the two classes reveals the preference of respondents in each class. Respondents in the first class seem less interested in V2G vehicles. They have significant and negative coefficient for the V2G dummy variable and most of the coefficients for the contract term attributes are statistically insignificant. On the other hand, respondents in the second class seem to be very interested in V2G vehicles. They have positive and significant coefficient for the V2G dummy variable and all of the coefficients for the contract term attributes are significant.

The number of classes we found in this study is the same as the number of classes we found in our study of conventional EVs (Hidrue et al, 2011). The characteristics of the preference classes are also similar in both studies. This is not surprising since V2G vehicles are also EVs. Consistent with our naming of the classes in the conventional EV study, we labeled respondents in the first class as GV-oriented respondents and respondents in the second class as EV-oriented respondents.

Class Membership Model

Table 6 presents results from the class membership model. The model normalized the parameter vector for the GV class and estimated the parameters for the EV class. Hence, the estimated parameters represent the contribution of the class membership variables on the likelihood of being in the EV class. For example, the parameter for young (18 – 35 years of age) is positive and significant. It indicates younger respondents are more likely to be in the EV class than older respondents (>55). The impact of the class membership variables on the likelihood of being in the GV class is simply the opposite of their impact on the EV class, since the probability of membership into the GV class is one minus the probability of membership into the EV class. Table 6 also presents the odds ratio estimates of the coefficients. The odds ratio 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 1.9 for young indicates that a person of age between 18 and 35 is 1.9 times more likely to be in the EV class than a person over 55.

Many of the variables we used in the class membership model are significant and have the right sign. We used three dummies to measure the effect of age on class membership. Younger drivers (18-35) are more likely to be in the EV class than older drivers (>55). Middle age drivers (36-55) have also higher likelihood of being in the EV class than older drivers, but the difference is not statistically significant. Drivers who expect gasoline prices to increase in the coming five years are more likely to be in the EV class. This makes sense since EVs do not use gasoline. Green consumers are also likely to be in the EV class. To measure consumers' greenness, we asked respondents to indicate how much change they made in their life style and shopping habit in the last five years. Those who indicate they made major changes or minor changes are more likely to be in the EV class than those who indicate they made no changes. People who plan to buy hybrid cars and people who have a place at home to install EV outlet are more likely to be in the EV class. Early adopters – those who buy new products that come to the market – are also more likely to be in the EV class.

All of the variables discussed above have the expected impact on class membership. Few other variables in Table 6 require explanation. Making one or more long drives a month increases the likelihood of being in the EV class. One might have expected that people who make more long drives would be less inclined to buy an EV due to issues related to driving range. The positive sign for this variable, which we also saw in some of our pretests, may come from an interest in saving fuel. People traveling longer distances pay more for fuel and stand to save more from EVs. The V2G vehicle as described in our survey has also 200 miles of driving range, which is reasonable for most drivers. Male drivers are also more likely to be in the EV class than female drivers. We don't have a good explanation why this is so. In our conventional EV study, gender was not significant. Several demographic variables are not significant: income, being in multicar household, having college education, and size of the vehicle a respondent plans to purchase.

Looking at the odds ratio column, we see having a plan to buy a hybrid vehicle, having a place to install EV outlet at home, and having a green life style are the biggest predictors of membership into the EV class, with 2.7, 2.6 and 2.7 odds ratio, respectively. Being young driver and being an early adopter are next highest predictors with 1.9 and 1.7 odds ratio, respectively.

Conditional Random Utility Model

We used four attributes to estimate the choice of V2G vehicles: price difference between a V2G vehicle and the respondent's preferred GV, annual cash back on V2G contract, guaranteed minimum driving range (GMR), and required plug in time per day (RPT). The levels used for each attributes are given in Table 1. We specified price and cash back as continuous variables, and GMR and RPT as class variables. The latter specification is based on Wald and log likelihood ratio tests which indicate non-linear effect of these two attributes on V2G vehicle choice. In estimating the model, we used the most preferred levels of GMR and RPT as a reference level. This means, the parameter estimates for these attributes are expected to have a negative sign.

Table 7 presents the estimated parameters. For comparison purposes, parameter estimates from a multinomial logit (MNL) version of the model are also presented. Except one, all parameters have expected signs. Also, the relative size of the parameters for the attributes specified as class variables (GMR and RPT) perform as expected. For example, the coefficient estimates show a preference ordering for RPT that decreases consistently as the number of required plug in time increases. This basic step-wise consistency holds for both attributes across the two classes as well as in the MNL model.

Comparing the results of the MNL model and the LC model shows the advantage of the LC model over the MNL model. First, the LC model provides statistically better fit than the MNL model. A Log likelihood ratio test showed the difference in model fitness is statistically significant. Second, the LC model revealed significant preference heterogeneity in the data. In the presence of such heterogeneity, parameter estimates from MNL model are biased estimates.

Table 7 shows price is statistically significant and negative in all instances, showing vehicle price is clearly an important predictor of V2G vehicle choice, as one would expect. The coefficient on cash back is positive and significant in all models, indicating that more revenue from providing reserve services makes one more likely to choose a V2G vehicle.

Table 7 also presents implicit prices for each class as well as a probability weighted average prices for the entire sample. 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 class by the probability of class membership. Comparing the implicit prices between the two classes of the LC model shows considerable preference heterogeneity in the population. The coefficient of the V2G constant, for example, is positive and significant for the EV class, but negative and significant for the GV class. The value of the V2G constant represents premium a respondent would pay or compensation a respondent would require to switch from the respondent's preferred GV to a comparable V2G vehicle, ignoring adjustment for cash back (the attribute modeled as continuous variable in the model). This V2G vehicle has 200 miles of driving range on a full battery, it takes 4 hours to full charge the battery, has better acceleration than a GV (5% faster), has lower pollution than a GV (75% lower), fuel costs like $1.00/gallon of gasoline, and has a contract term that requires 5 hour of rpt time and 175 miles of GMR. Respondents in the EV class would pay a premium of $23,667 to switch from their preferred GV to this V2G vehicle whereas respondents in the GV-oriented class would ask a compensation of $4,414. This big difference in willingness to pay (WTP) is a reflection of the difference in preference for the EV attributes of the vehicle as well as for the binding nature of the V2G contract. In the same study we conducted about conventional EVs, we found significant heterogeneity for driving range, charging time, pollution reduction, fuel saving as well as acceleration (see Hidrue et al, 2011).

Respondents in the two classes also differ in how they value cash back. Relatively, those in the GV class discount cash back more than do those in the EV class. For respondents in the EV class, annual cash back of $1,000 over the life of the car is worth around $2,000 in present value, but the same money is worth only $700 for those in the GV class. Despite this difference, respondents in both classes discount cash back heavily. This could be due to perceived risk of the V2G technology or its value. It may also be due to respondents' mistrust of electric power companies, as some people indicated in our focus group discussion.

Finally, consumers in the two classes also differ in how they value GMR and RPT. All coefficients for these attributes are statistically significant for the EV class, but only one coefficient is significant for the GV class. The difference in statistical significance is, perhaps, a reflection of difference in interest in the V2G concept. That is, respondents in the EV class are interested in the idea and changes in the contract terms drove their decision, making the coefficients statistically significant. Respondents in the GV class, on the other hand, are not interested in the V2G idea, and changes in the contract terms were inconsequential in their choice.

The implicit prices in Table 7 show respondents associate high inconvenience cost with signing V2G contracts. The implicit prices for GMR and RPT measure drivers' perceived inconvenience cost of signing V2G contracts. The reference level for GMR is 175 miles. For the average person (combining GV and EV classes), reducing GMR from 175 miles to 75 miles is equivalent to increasing the initial price of the car by $3,124. Reducing it further to 25 miles is equivalent to $5,699 increase in initial price. Note that the costs increase at an increasing rate, showing non-linear effect of GMR on V2G choice. The per-mile costs are $31.2 per mile (in the range 175 to 75 miles) and $51.5/mile (in the range 75 to 25 miles). For RPT, the reference level is 5 hours per day. Again, taking the average person, increasing RPT from 5 hours to 10 hours is equivalent to increasing initial price by $2,091. Increasing it further to 15 hours and 20 hours is equivalent to increasing initial price by $4,180 and $6,950, respectively. The per-miles incremental costs are $418.2/mile (5 to 10 hours), $417.8/hour (10 to 15 hours), and $554/hour (15 to 20 hours).

Are these estimates reasonable figures? The best way to gauge the reasonableness of the above estimates would be to compare them with real world data. However, such data does not exist. In the absence of real world data, we compared the above estimates with estimates from our conventional EV study. Both studies have some measure of driving range and vehicle time. While such comparison may not help to establish credibility of drivers' actual payments, it does serve to assess the consistency of respondents' valuation across the two choice experiments.

First we consider the value of driving range. In the conventional EVs study, we estimated the value of driving range on full battery and in the V2G vehicle study we estimated the value of guaranteed minimum driving range. Full-battery driving range is a true upper bound on distance, whereas the GMR is a minimum set by contract to insure that the power system's use of the battery will never result in a partially-filled battery with less than that amount of guaranteed minimal range. The GMR will only occasionally be realized over a month, and respondents were told they could always skip contract terms on days of heavy driving requirements. Hence, we expect drivers to have higher value for increasing driving range than for increasing GMR. The estimates we found confirm this expectation. In the conventional EV study, we found the value of increasing driving range by one mile in the range of 75 miles to 200 miles is $74. For a similar range (75 miles to 175 miles), we found the value of increasing GMR by one mile is $31.2. This comparison confirms our expectations that the two are in the same order of magnitude. Physical reduction in battery size has twice the cost of a reduction in GMR, nevertheless, a GMR that reduces the guaranteed range considerably reduces the value. Even though the drivers can opt out on days of expected trips, or can charge up if the GMR has not left enough for an unplanned trip, the substantial reduction in value suggests that they do not see GMR as a part of a range management strategy, rather they see it as a range limitation comparable to a smaller battery.

We also have estimates of the value of vehicle time in both studies. In the conventional EV study, we estimated the value of decreasing charging time. In the V2G study, we estimated the value of required plug-in time (RPT) under the V2G contract. The comparison gives us a sense of how respondents value RPT. If respondents treat RPT as idle time, during which they are not using the car anyway so they might as well extract value from V2G, then the disamenity value of RPT we would expect be much lower than the disamenity value of longer charging time. On the other hand, if respondents treat RPT as time taken out of their active driving period, the two estimates will be close to each other. In any case, since drivers can sometimes skip V2G contract, the disamenity value of RPT should not be greater than the disamenity value of charging time. The common time we have estimates in both studies is 5 to 10 hours of charging time and of RPT. For this range of time, we found the values are very close to each other, with the disamenity value of an hour of charging time slightly higher than the value of an hour of RPT ($427/hour versus $417/hour).

The above comparison for vehicle time shows drivers do not perceive RPT as idle time. This means that they will consider a contract for required plug in time to be a substantial disamenity. On the other hand, a contracting aggregator or grid operator would like to have both some assurance of staying plugged in, and a motivation from the driver to do so. However, we find that, even though US vehicles are parked, on average, 23 hours a day, our estimates show they associate high inconvenience cost for agreeing in advance to stay plugged-in, even for 5 to 10 hours per day. This finding implies that to increase the competitiveness of V2G power on the market, power aggregators should avoid asking respondents to sign contracts and instead allow them to provide the service when they are able.

VI. Can V2G Revenues Help Improve the Market for EVs?

In the previous section, we have seen that respondents associate high inconvenience cost with signing V2G contracts and apply a high discount rate to anticipated revenue earned from V2G services. This raises the question of whether designing EVs with V2G capability will help EVs in the market. That is, will designing EVs with V2G capabilities help or hurt them? In principle, the answer to this question is simple. If the revenue drivers earn from providing reserve service is large enough to compensate for the inconvenience cost they perceive in providing reserve service, designing EVs as V2G vehicles will help them. On the other hand, if the revenue they earn is not large enough to compensate for the perceived inconvenience cost, then designing them as V2G vehicles will not help them. Hence, the question boils down to whether the revenue V2G vehicles can earn on the power market is large enough to compensate for the perceived inconvenience cost. In this section, we will try to answer this question by comparing the inconvenience cost of signing V2G contracts (implicit contract prices) implied by our estimates with the potential revenue that can be earned in the power market.

We start by establishing the decision making framework for signing V2G contracts. A person will sign a contract to provide reserve service from her V2G vehicle if the value of the revenue she earns is greater than the perceived inconvenience cost of providing the service. The inconvenience costs of signing a contract are measured by the length of the RPT and the reduction in GMR. The price of a given contract is the amount of cash back (CB) that will leave a person indifferent between signing a contract or not. In our model, that is the value of CB that solves the following equation in each class:

$$\beta_{cb}CB_n - \beta_{gmr}GMR_n - \beta_{rpt}RPT_n + \varepsilon_{1,n} = \varepsilon_{0,n}$$

$$CB_n = \frac{\beta_{gmr}GMR_n + \beta_{rpt}RPT_n + (\varepsilon_{0,n} - \varepsilon_{1,n})}{\beta_{cb}} \tag{6}$$

Where ε_{1n} and ε_{0n} are stochastic utilities associated with and without signing a contract, respectively. Equation (6) is used to calculate annual cash back for individual *n* in class S. However, class membership is probabilistic: the individual belongs to class *S* with probability Q_s. Following Boxall and Adamowicz (2002), we used the following formula to calculate weighted average annual cash back across the two classes:

$$CB_{n|weighted} = P_{ev}CB_{n|ev} + (1 - P_{ev})CB_{n|gv} \tag{7}$$

Where P_{ev} is probability of membership in the EV class and $(1\text{-}P_{ev})$ is probability of membership in the GV class.

We used equation (7) to calculate contract prices for several scenarios of V2G contracts. Table 8 presents these contract scenarios and the corresponding contract prices. These contracts are constructed from the levels of RPT and GMR used in our survey. In constructing the scenarios, we have used all four levels of RPT (5, 10, 15 and 20 hours) and two levels of GMR (25 and 75 miles). We did not use the other two levels of GMR (125 and 175 miles) because we wanted to stay within the driving range of current EVs. In any V2G contract, the driving range of the vehicle has to be greater than the GMR. Most current EVs have less than150 miles of driving range. Since the coefficients for GMR and RPT are relative to the reference level of each attribute, the contract price estimates in Table 8 are incremental prices required to upgrade the contract from the base level contract (5 hours of RPT and 175 miles of GMR) to the levels in each contract scenario. Also, note that since cash back is defined on annual basis in our survey, the estimated contract prices represent annual contract prices. Finally, since we observe each respondent in our model as partly EV-oriented and partly GV-oriented, the contract prices reported in Table 8 are probability weighted average prices for the two classes.

The estimates in Table 8 show drivers will require anywhere from $1850 to $8801 in payments, depending on the specification of the contract. Figure 2 also presents the estimated annual contract prices in the form of box-and-whisker plots. The plots show two parallel lines: one for the 75 miles of GMR and one for 25 miles of GMR. The plots show when GMR decreases from 75 miles to 25 miles, on average, we predict that drivers would require a higher contract price by $1696. The plots also show contract prices increase rapidly as the length of RPT increases. Increasing RPT from 5 hours to 10 hours requires additional $1170 in annual contract price. Further increase in RPT from 5 hours to 15 hours and 20 hours requires additional $2860 and $5254 in annual contract price, respectively. These estimates also show strong non-linear effect of RPT. The per-hour incremental costs are $234 (between 5 and 10 hours), $338 (between 10 and 15 hours), and $478 (between 15 and 20 hours). These estimates show that it is cheaper to set the RPT at a lower level. For example, if these were the values required by consumers, it would be cheaper for aggregators to sign two drivers at 10 hour of RPT each than to sign a single driver for 20 hour of RPT.

The contract prices in Table 8 represent the annual cash back payments that will make the average driver indifferent between signing a V2G contract or not. At those prices, the average driver is indifferent between the value of the cash back from the contract and the inconvenience cost associated with the contract. For drivers to buy EVs because of their potential ability to earn cash back, the cash back they earn have to be greater than the amounts reported in Table 8. Can V2G vehicles earn the amounts reported in Table 8 in the market? The revenue a V2G vehicle can earn depends on many factors including the type of power market (spinning power vs regulation power), the region of the country (power markets vary by region), power capacity of the connection, hours connected, etc. However, given the estimates in Table 8, it is possible to make a general assessment. Here, we use a study by Kempton and Tomic (2005) to assess the feasibility of earning our estimates in the market.

Kempton and Tomic (2005) estimated the potential net revenue a Toyota RAV4 EV can earn on the power market. They calculated net revenue as revenue net of depreciation and other equipment costs associated with providing reserve service. Their calculation does not account for the inconvenience cost drivers perceive in signing contracts. Kempton and Tomic (2005) assumed 18 hours of RPT and 20 miles of GMR. 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), a Toyota RAV4 EV could earn net revenue of $2,554 annually. In 2009 dollars, this corresponds to $2972. Table 8 shows the corresponding contract price, the price for reducing GMR from 75 to 25 miles and increasing RPT from 5 to 20 hours, is about $6951, which is much higher than the net revenue estimates from Kempton and Tomic (2005).

The above comparison shows, under a contract arrangement, the V2G concept is unlikely to help EVs in the market since the potential revenue that can be earned is much lower than what drivers are asking to provide the service. The main reason for the high contract price is the high inconvenience cost drivers associate with signing V2G contracts. For the V2G concept to help EVs in the market, this suggests that power aggregators should avoid requiring drivers to sign contracts and instead allow them to provide the service at their convenience. The main reason for having V2G contracts is to allow power aggregators predict the amount of reserve power they can deliver to the market. If power aggregators can predict the number of cars parked each hour of the day and predict the next days' daily driving requirement of each vehicle from historical data, then they can predict the amount of power they can deliver to the market and eliminate contracts completely. In such a model, drivers would be paid for the number of hours they made their car available to provide reserve service and for the amount of energy they allowed power companies to draw from their car's battery rather than on the basis of a pre-specified contract term. This will eliminate the high anticipated inconvenience cost drivers assign to contracts and make V2G more attractive to drivers.

VII. Conclusion

In this paper we presented the first study of demand for V2G enabled EVs. We studied consumers' preference for different contract term arrangements, and we found that drivers associate high inconvenience cost with signing V2G contracts. This is probably due to a combination of drivers' desire for flexibility in car use, an unawareness of how many hours their cars are parked, how to opt out of some contract terms, etc. We also found drivers discount revenue from V2G 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 high price to sign V2G contracts, which will reduce the competitiveness of V2G power in the power market. Therefore, for V2G capabilities to help EVs in the market, our analysis suggests that contract terms should be eliminated.

Appendix

Table 1: Attributes and Levels Used in the Choice Experiment

Attributes	Levels
Minimum guaranteed driving range (GMR)	25 miles 75 miles 125 miles 175 miles
Length of 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 between alternatives at the following levels	
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: Distribution of Choices among Alternatives

Alternatives	**Without yea-saying correction (%) N=1996**	**With yea-saying correction (%) N=1033**
V2G vehicle-1	22.5	20.9
V2G vehicle-2	30.0	31.1
My Preferred Gasoline Vehicle	47.5	25.7
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	-	22.3
Total	100	100

Table 3: 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 4: Definition and Descriptive Statistics (N=3029) for Variables Used in LC Model. Either percent (%) or mean is shown, depending on whether the variable is dichotomous or not.

Variable	**Description**	**% in Sample**	**Mean (SD)**
Young	1 if 18-35 years of age; 0 otherwise	30	
Middle age	1 if 36-55 years of age; 0 otherwise	43	
Old	1 if 56 years of age or above; 0 otherwise	27	
Male	1 if male; 0 otherwise	43	
College	1 if completed a BA or higher degree; 0 otherwise	37	
Income	Household income (2009 $)		$60,357 ($42,398)
Gas price	Expected price of regular gasoline in 5 years ($)		$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 5: Information Criteria for Selecting Number of Classes

Number of classes	**Number of parameters**	**LL(β)**	**AIC**	**CAIC**	**BIC**
2	36	-4756.7	9585.4	**9863.0**	**9826.9**
3	62	-4784.5	9693.0	10171.0	10109.0
4	88	-4656.4	**9488.8**	10167.0	10079.2

Table 6: Class Membership Model (GV class is the excluded class)

Variables	**Coefficient**	**T-Stat.**	**Odds Ratio**
Class membership constant	-2.5	-11.1	0.08
Young [1]	0.65	5.3	1.9
Middle age[1]	0.20	1.8	1.2
Male	0.34	3.7	1.4
College	0.14	1.5	1.2
Income (in 000)	-0.0017	-1.5	0.99
Gasoline price (in $/gall)	0.05	2.0	1.05
Hybrid	0.99	9.8	2.7
Outlet	0.95	9.1	2.6
Multicar	-0.004	-0.04	0.96
Small car[2]	0.22	1.7	1.2
Medium car[2]	0.12	1.2	1.1
Long drive	0.25	2.6	1.3
Major green[3]	1.01	7.1	2.7
Minor green[3]	0.64	5.4	1.9
New goods	0.51	5.8	1.7
Log likelihood value	-4757		
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: Conditional Random Utility Model and Implicit Price Estimates
(T-stat. in parenthesis)

Attributes	Parameters			Implicit Prices		
		LC Model		LC Model		
	MNL Model	GV-Class	EV-Class	GV-Class	EV-Class	Weighted Average
V2G constant	-1.5	-2.31	2.28	-$4,414[1]	$23,667[1]	$12,675[1]
	(-8.3)	(-2.1)	(26.6)			
Yea saying tendency	-0.21	-0.25	-0.15			
	(-3.3)	(-0.95)	(-1.65)			
Price (000)	-0.08	-0.58	-0.09			
	(-22.1)	(-4.0)	(-32.4)			
Cash Back (000)	0.17	0.42	0.19	$0.72	$2.1	$1.51
	(12.4)	(3.9)	(15.1)			
GMR[3] (excluded category is 175 miles)						
125 miles	-0.05	0.60	-0.15	$1,034[2]	-$1,667	-$500
	(-0.8)	(0.89)	(-3.0)			
75 miles	-0.30	-0.55	-0.43	-$948[2]	-$4,778	-$3,124
	(-5.2)	(-1.3)	(-8.6)			
25 miles	-0.69	-1.21	-0.77	-$2,086[2]	-$8,556	-$5,699
	(-9.9)	(-1.5)	(-13.4)			
RPT[3] (excluded category is 5 hours)						
10 hours	-0.12	-0.18	-0.31	-$310[2]	-$3,444	-$2,091
	(-2.1)	(-0.22)	(-6.0)			
15 hours	-0.35	-1.3	-0.51	-$2,241[2]	-$5,667	-$4,180
	(-5.8)	(-1.6)	(-9.6)			
20 hours	-0.67	-2.9	-0.76	-$5,179	-$8,444	-$6,950
	(-10.5)	(-4.8)	(-14.4)			
Log likelihood value	-5429	-4929				
Sample size	6058	6058				

1. Yea-say correction turned on in all cases.
2. Based on a statistically insignificant parameter at the 5% level of confidence.
3. GMR= guaranteed minimum driving range; RPT=Length of required plug-in time per day

Table 8: Implicit Annual Contract Prices

Contract Term Scenario	GMR	RPT	Annual Contract Prices
A	75 miles	5 hours	$1,850
B	75 miles	10 hours	$3,023
C	75 miles	15 hours	$4,713
D	75 miles	20 hours	$7,106
E	25 miles	5 hours	$3,547
F	25 miles	10 hours	$4,719
G	25 miles	15 hours	$6,408
H	25 miles	20 hours	$8,801

Choice 1 of 2 Choices

You indicated earlier that your next purchase would most likely purchase would most likely be an SUV and that you would spend $25,000 - $29,999. Suppose on your next vehicle purchase you were offered this vehicle plus two V2G electric version 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	**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	75 miles	175 miles	
Average Length of Required Plug-in time Per Day with Energy Dial Set to Sell on V2G Contract	15 hours	20 hours	
Cash Payment Made to You on V2G Contract	$1,000/year	$,5000/year	
Price Compared to Your Preferred Conventional Gasoline	same	$16,000 higher	

I would most likely Purchase….

. V2G Electric Vehicle 1
. V2G Electric Vehicle 2
. My Prefered Conventional Gasoline Vehicle
. My Prefered Conventional Gasoline Vehicle – Although I like the idea of V2G electric vehicles and some of the features here are OK, I could/would not buy these V2G electric vehicles at these prices

Figure 1: Sample V2G Choice Exercise

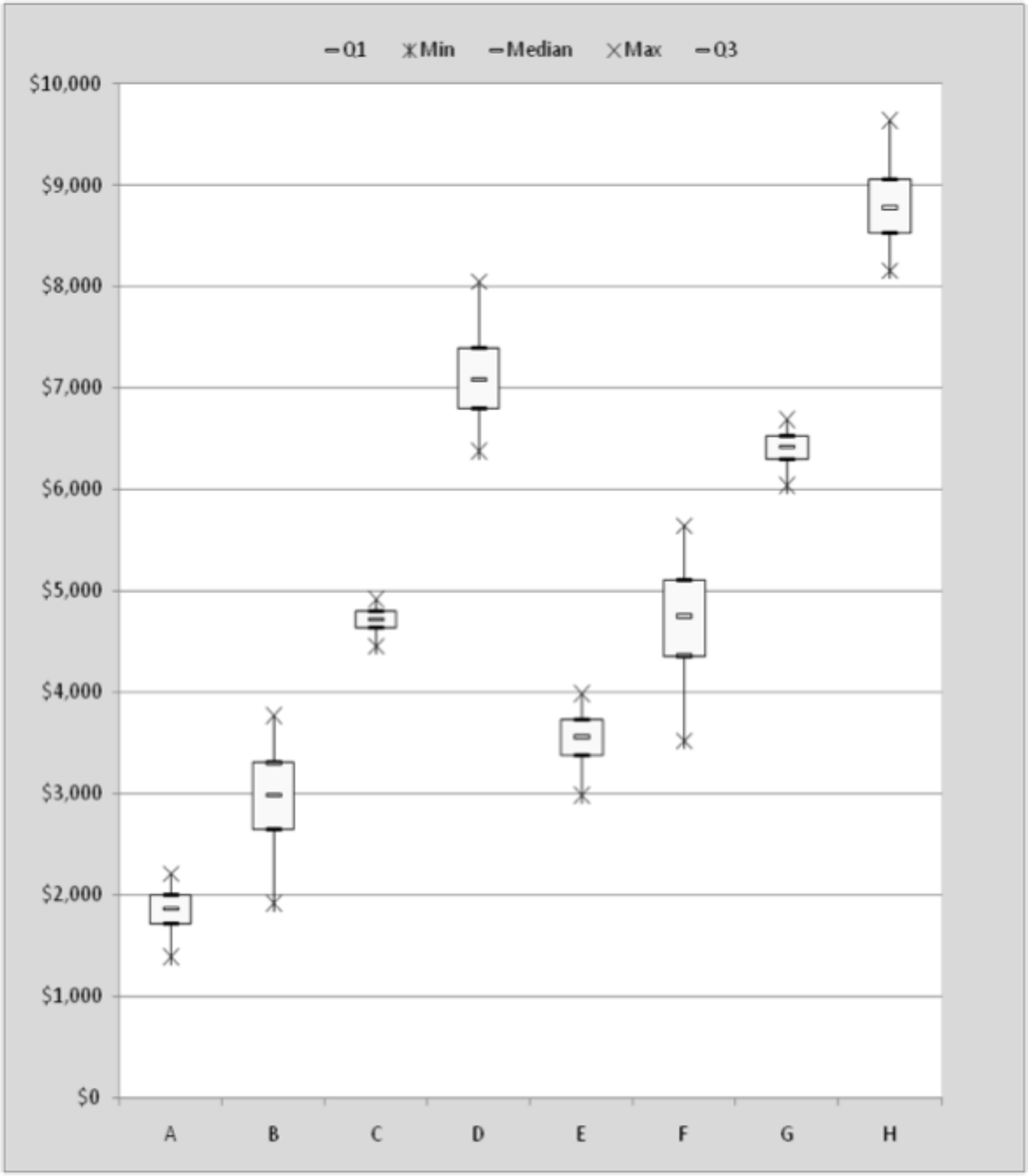

Figure 2: Box-Whisker Plot for the Eight Contracts A – F, Shown in Table 8

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