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Willingness to pay for vehicle-to-grid (V2G) electric vehicles and their contract terms

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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 the grid needs reserve power. Since providing this service can lead to payments to owners, it effectively reduces the life-cycle cost of owning an electric vehicle. Using data from a national stated preference survey, this paper presents a study of the potential consumer demand for V2G electric vehicles. In a 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 that the V2G concept is most likely to help EVs on the market if power aggregators operate either on pay-as-you-go basis (more pay for more service provided) or provide consumers with advanced cash payment (upfront discounts on the price of EVs), rather than imposing fixed requirements on participants.

1. Introduction

Vehicle-to-grid (V2G) power is a new concept in electric vehicle (EV) design. It involves designing EVs so that they can discharge power stored in their batteries back to the electric grid. An electric vehicle with V2G capability has controls that enable 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 added power capacity. With proper technology, EVs may be able to provide reserve service at a lower cost and pay the owners of EVs for the service (Guille and Gross, 2009; Kempton and Letendre, 1997, and Kempton and Tomić, 2005).[1]

Designing EVs with V2G capability has two advantages. First, payment to owners of EVs for power stored in their vehicles may help lower the overall cost of ownership of EVs, which is currently well above the market price of gasoline vehicles (GVs). Kempton and Tomić (2005), for example, estimated that a Toyota RAV4 EV could earn up to $2554 annually from providing reserve service to the electric grid. Second, designing EVs with V2G capability may increase 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, which 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 could be used in tandem with wind and solar power for storage during periods of high output and for reserve power during periods of low output. Offsetting the environmental benefits to some extent is a shorter life expectancy for batteries in V2G vehicles versus conventional EVs. This is due to accelerated battery wear caused by an increased cycling of the battery, which in turn means higher effective battery cost for the consumer and more battery disposal.

The potential benefits of V2G electric vehicles have already attracted the interest of policy makers and power companies. However, little is known about consumer interest in such vehicles. Will consumers embrace the idea of selling power to the power sector? If so, at what price? Can revenue earned from such a plan help EVs on the market? While there is sizable literature on consumer choice for electric vehicles, we focus on these questions and consumers' choices vis-à-vis V2G

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[1] The first market participation of a group of V2G-EVs was in 2013 (Wald, 2013).

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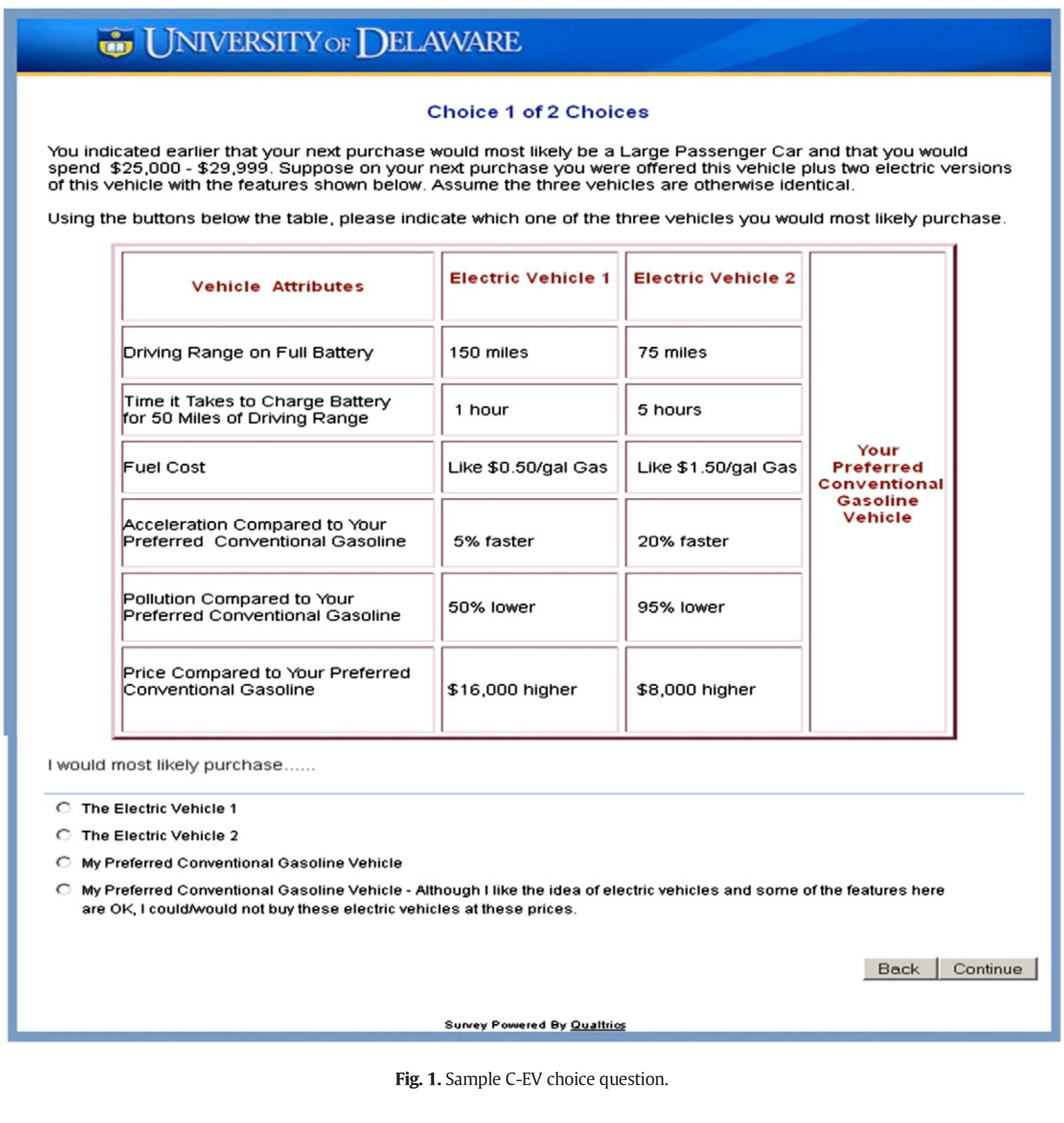
contact terms. Beggs et al. (1981), Calfee (1985), Bunch et al. (1993), Kurani et al. (1996), Tompkins et al. (1998), Brownstone and Train (1999), Ewing and Sarigollu (2000), Dagsvik et al. (2002), Hidrue et al. (2011) and Dimitropoulos et al. (2011) are good examples of choice modeling applications to electric vehicles.

To help answer some of these questions, we administered a web-based stated preference survey of U.S. households. A total of 3029 respondents randomly selected from a national sample completed the survey. The survey had three parts: a choice experiment for conventional electric vehicles with no V2G capability (hereafter C-EVs), a choice experiment for V2G electric vehicles (hereafter V2G-EVs), and a contingent valuation question for a prototype V2G-EV. 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 et al., 2011). This paper is a follow-up focusing on the V2G-EV choice data in the second part of the survey.

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 by identifying two groups with different sensitivities to the alternative attributes. We also considered other models to capture preference heterogeneity (mixed logit and standard logit with interactions between vehicle and individual characteristics). In our judgment the latent class model did the best job of capturing heterogeneity. 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. Guaranteed minimum driving range promises that car owner that his/her vehicle would always have at least a given number of miles of charge available (expressed as miles of minimum driving range). These features capture properties desired by the power sector to have greater certainty about the availability of power from parked cars.

This paper contributes to the literature on EVs and stated preference methods in at least four ways. First, even though the potential contribution of the V2G concept to EVs has been extensively discussed in the literature, this is the first paper to empirically evaluate whether V2G power helps EVs on the market. Second, our findings call into question the basic assumption that V2G's availability requirements should be of little consequence to consumers since cars are driven only a small fraction time on most days and for less than 30 miles per day. On the contrary, we find that consumers are extremely sensitive to V2G restrictions. Third, we propose two alternative V2G contract types based on our results, which may be more promising for V2G initiatives than conventional approaches. The conventional thinking in the V2G literature is that drivers sign pre-specified contracts in return for annual cash payments. We simulated several such contracts and found that these approaches are unlikely to make V2G power competitive under current market conditions. We propose other contract approaches that can appeal to drivers and may make V2G power more competitive.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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	
Driving Range on Full Battery	150 miles	75 miles	Your Preferred Conventional Gasoline Vehicle
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	

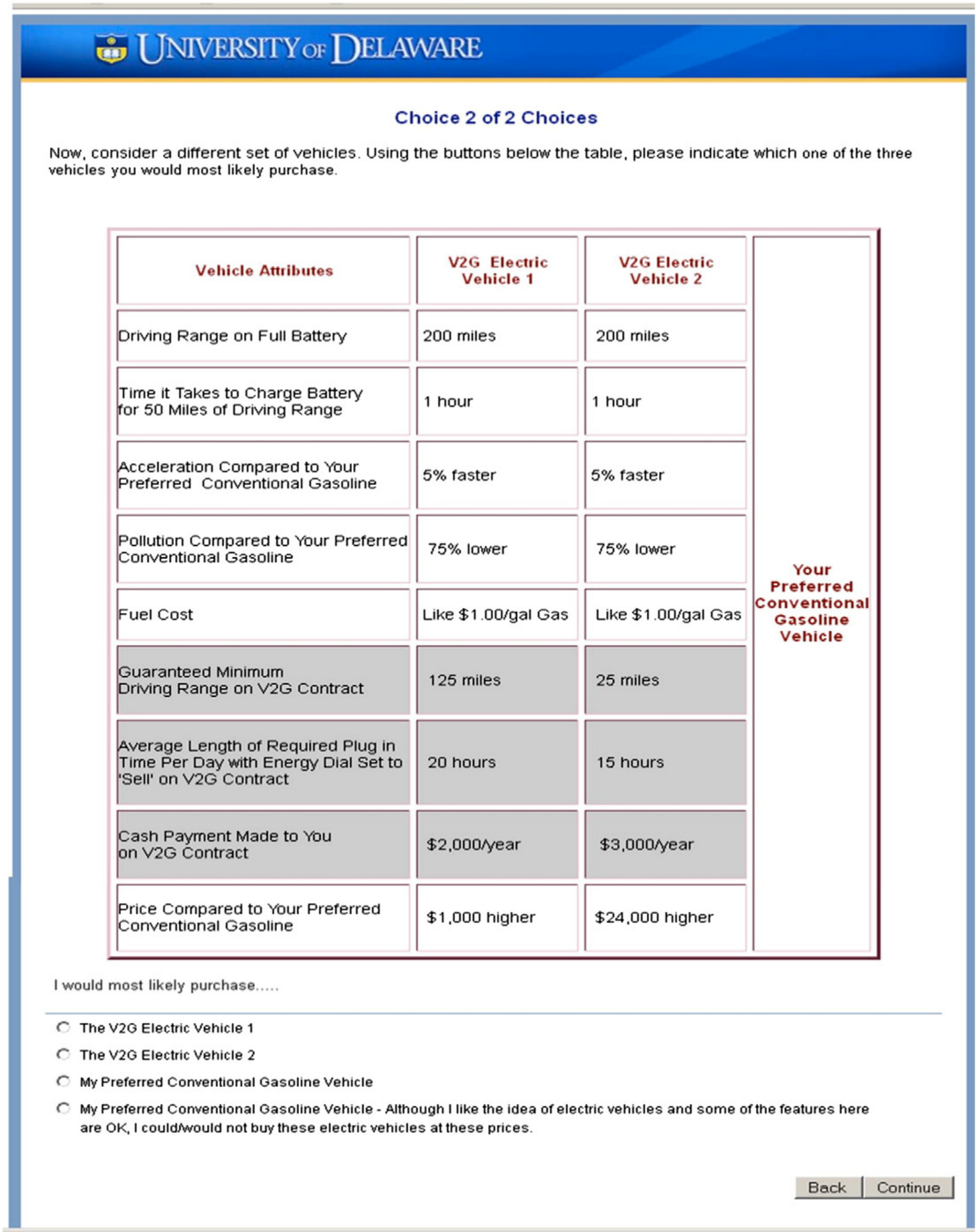
I would most likely purchase......

- 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

Fig. 1. Sample C-EV choice question.



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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

Fig. 2. Sample V2G-EV choice question.

Finally, on the methodological front, we use a two-step choice experiment as a way to convey complex products to survey respondents in a simple way. We believe the approach has promise in other settings.

The paper proceeds as follows. We discuss the V2G concept in the next section and follow that with sections covering study design, model, results, and potential for V2G to help electric vehicles on the market.

2. 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 (Pearre et al., 2011). 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 added power capacity is used for reserves and for balancing power. 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, the size of the vehicle's battery, the power of the charger, the vehicle's daily drive, and the type of power market. Generally, the value of the grid reserve service is greater the longer the car is available, the larger the size of the battery, the higher 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 Tomić (2005).

In most TSO markets, the highest value markets for a V2G-EV are the ancillary services markets (A/S), called regulation and spinning reserves. 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 min per call) but has to be ready on standby 24 h a day, 7 days a week. Regulation reserve refers to a power capacity required to keep generation and load in balance on a continual basis. Power companies smooth the difference between generation and load 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 h a day, 7 days a week, and TSOs buy from multiple generators to insure continuous availability.

Spinning reserve and regulation are paid by capacity (kW)—that is, they are paid by the assured 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 Tomić, 2005). Because A/S markets like spinning reserves and regulation have minimum capacity requirements to bid, 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 non-contractual variant, drivers would have no obligation to provide reserve service, rather 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 great certainty of power capacity to the aggregator. In this study, we follow a business model assuming a contract, where each V2G vehicle owner signs a contract with a power aggregator.

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 h 10 h 15 h 20 h
Annual cash back payment (CB)	$500 $1000 $2000 $3000 $4000 $5000
Price relative to your preferred GV (ΔP)	Same $1000 higher $2000 higher $3000 higher $4000 higher $8000 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 h
Acceleration relative to your preferred GV	5% faster
Pollution relative to your preferred GV	75% lower
Fuel cost	Like $1.00/gal gas

3. 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 their attributes and another covering 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 et al. (2011). Louviere and Hensher (1983) and Louviere et al. (2000) are sources for background on choice experiments.

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. Our motivation stems from focus group results and from the literature on complexity in choice experiments (Arentze et al., 2003; Caussade et al., 2005; Deshazo and Fermo, 2002; Mazzotta and Opaluch, 1995; Stopher and Hensher, 2000; Swait and Adamowicz, 2001). The focus groups strongly support separating the C-EV and V2G-EV choices. The findings in the literature do not suggest the two-part strategy directly but do generally favor limiting the number of attributes in any given choice question. By separating our choices we achieve this result.

The first part of our survey, pertaining to C-EVs, described and compared C-EVs to gasoline vehicles (GVs). Respondents were given two choice experiments in which they made a choice between their preferred GV and two C-EVs of similar configuration (see Fig. 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 contract.

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 in the choice experiment were described as V2G-enabled electric versions of their preferred GV. Respondents were

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

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 Fig. 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.

A drawback of this approach is that we do not directly 'observe' tradeoffs people may make between V2G contract terms and C-EV attributes. These are inferred using relative coefficient sizes between the two models. The tradeoff of most concern and missed in this analysis is the interaction between charging time and guaranteed minimum driving range (GMR). For example, drivers may be less concerned about GMR if they have fast charging time (10 min rather than the 1 h used in our survey). By holding charging time fixed at 1 h in all cases, our analysis misses this possible effect.

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 annual 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 a driving-distance-equivalent charge on a battery below which power aggregators promise not to draw power from a car's battery. For example, the power company may promise never to let the battery fall below a charge sufficient for 25 miles of driving. This gives car owners a guaranteed minimum driving range even if the power company is drawing energy. It is different from driving range on a full battery used in the C-EV choice experiment, which indicates the distance the vehicle can drive on a full battery charge. Respondents were told that power companies would rarely draw the battery down to its minimum level and that owners 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. 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 aggregators would set these requirements to establish the viable storage capacity of a fleet of vehicles. The larger the required 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 "macro functions" available in SAS to configure our choice experiment (Kuhfeld, 2005). The process involves two steps. First, we used the "%MktEx macro function" to generate candidate choice set profiles. This macro uses the number of levels for each attribute to generate candidate number of profiles for a linear design. In our case, the macro found an optimal linear design (100% D-efficiency) with 36 profiles. Next, we used the "%ChoicEff macro function" to generate an efficient design for a choice models (nonlinear designs). This macro uses the candidate profiles from step one, an assumed model, and parameters for each attribute level to generate efficient choice design or profile combination.

The main challenge in developing the profile 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 final pretest. A total of 243 respondents participated, each answering two choice questions. This gave us 486 observations, which we used to estimate a simple multinomial logit model. The parameter estimates were then used as the priors in developing the final choice design. The 36 profiles were grouped into 18 unique blocks or choice pairs. The blocks were then randomly assigned to respondents in the survey.

Finally, we also included a treatment for yea-saying in our choice experiment (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 make a purchase. To test for this effect, one-third of our sample received a response format in their choice questions that allowed us to identify yea-saying. The other two-thirds of our sample received a conventional response format without the correction.

The correction was a dissonance-minimizing response option (Blamey et al., 1999). People were given two options for choosing a GV. One option was "I would most likely purchase my preferred conventional gasoline vehicle." The other (using dissonance minimizing) was "I would most likely purchase 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". The last response option shown at the bottom of Figs. 1 and 2 is our correcting format. It essentially allowed people to say "I like the idea of V2G" (registering favor with concept) "but not at these prices" (showing their true likelihood of purchase).

Table 2 presents the frequency of choices for the two samples. Although a large share of the sample with the correction chose the yea-say response in the V2G-EV experiment (22.3%), there appeared to be little yea-saying bias in our survey. Comparing the samples with and without the correction, the share of V2G-EV choices (either V2G vehicle-1 or V2G vehicle-2) is hardly changed by the yea-saying treatment—52.5% without the correction and 52.0% with the correction. Most of the votes for the yea-saying option, in other words, came from respondents who otherwise would have reported purchasing a GV.

4. Econometric model

We estimated a latent class random utility model using the survey data described above (Swait, 1994). Our choice of model was driven

[2] In retrospect it would have been better if we had created an attribute for the "number of days per month the battery is drawn down to its minimum" and modeled its effect directly. For example, levels might be 1, 3, 5, and 10 days per month on average where the battery would be depleted to some set minimum mileage.

Table 3
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 dollars)		\$60,357 (\$42,398)
Car price	Expected amount spent on next vehicle		\$23,365 (\$9607)
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 100 miles/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	

by a need to capture heterogeneity in V2G-EV choice. Latent class models capture preference heterogeneity by estimating separate models for different classes of consumers. The classes are determined econometrically by best fit. See Gopinath (1995), Walker (2001), Boxall and Adamowicz (2002), Greene and Hensher (2003), Provencher and Moore (2006), Walker and Ben-Akiva (2002), and Ben-Akiva et al. (2002) for examples and more on latent class and related models. Our model combines the C-EV choice data with the V2G-EV data and uses a structure much like that in Hidrue et al. (2011), where we only considered the C-EV choice data.

Our RUM model for an individual has the form

$$\begin{aligned} U_i &= \beta_0 d + \beta_p \Delta p_i + \boldsymbol{\beta}_\chi x_i + \boldsymbol{\beta}_y \boldsymbol{y}_i d + \varepsilon_i \\ U_0 &= \varepsilon_0 \end{aligned} \tag{1}$$

where $i = 1{,}2$ for the two EVs in the choice set and $i = 0$ for the GV. Δp_i is price difference between EV (C-EV or V2G-EV) and 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. β_0 is a constant that captures an average effect of V2G-EV versus C-EV. The errors terms ε_i and ε_i are assumed to have type-1 extreme value distributions with mean zero and standard deviation 1. This gives a multinomial logit probability of the form

$$L(\beta) = \frac{\delta_1 \exp\left(\beta_0 d + \beta_p \Delta p_1 + \boldsymbol{\beta}_x \boldsymbol{x}_1 + \boldsymbol{\beta}_y \boldsymbol{y}_1 d\right)}{I} + \frac{\delta_2 \exp\left(\beta_0 d + \beta_p \Delta p_2 + \boldsymbol{\beta}_x \boldsymbol{x}_2 + \boldsymbol{\beta}_y \boldsymbol{y}_2 d\right)}{I} + \frac{\delta_0}{I} \tag{2}$$

where $\delta_1 = 1$ if the respondent chooses EV1; $\delta_2 = 1$ if the respondent chooses EV2; $\delta_0 = 1$ if the respondent chooses GV; $I = 1 + \Sigma_{i=1}^{2} \exp(\beta_0 d + \beta_p \Delta p_i + \boldsymbol{\beta}_x \boldsymbol{x}_i + \boldsymbol{\beta}_y \boldsymbol{y}_i d)$; and $\beta = (\beta_0, \beta_p, \beta_x, \beta_y)$.

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

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

where the first term $\frac{\exp(\alpha^c \boldsymbol{z})}{\sum_{c'=1}^{C} \exp(\alpha^{c'} \boldsymbol{z})}$ is the probability of class membership and the second term $L(\boldsymbol{\beta}^c)$ is the logit probability from Eq. (2) now defined for each class c. The term $\boldsymbol{z}$ is a vector of individual characteristics; C is the number of latent classes; $\beta = (\beta^1,\ldots,\beta^C)$ so each class has its own set of random utility parameters; $\alpha = (\alpha^1,\ldots,\alpha^C)$; 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. Eq. (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.

5. Estimation results

5.1. Testing for scale differences

Because our model combines the C-EV and V2G-EV data sets, we tested for scale difference, or difference in error variance, between the two data sets. A scale difference between the two data sets may arise for a number of reasons—difference in number of attributes (6 vs 9), difference in vehicle types (C-EV vs V2G-EV), and difference in placement of questions in the survey (the C-EV always comes before the V2G-EV experiment). 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 through the paper.

5.2. Choosing number of preference classes

We estimated our model with 2, 3, and 4 classes and then compared them using two measures of fit: the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The 2-class model dominated. The 4-class model failed to converged. The 3-class model

Table 4
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[a]	0.72	5.6	2.1
Middle age[a]	0.22	1.96	1.2
Male	0.32	3.4	1.4
College	0.13	1.3	1.1
Income (000$)	−0.0023	−1.9	0.99
Gasoline price ($/gal)	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[b]	0.2	1.5	1.2
Medium car[b]	0.15	1.5	1.2
Long drive	0.29	3.0	1.3
Major green[c]	1.1	7.6	3.0
Minor green[c]	0.68	5.4	2.0
New goods	0.51	5.6	1.7
Log likelihood value	−9472.1		
Sample size	12,116		

See Table 3 for variable definitions.
[a] Excluded category is Old (>56).
[b] Excluded category is Large Car.
[c] Excluded category is Not Green.

Table 5
Parameter estimates and implicit prices for the C-EV portion of the latent class RUM model (t-statistics in parenthesis).

	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	−$2776	
	(−1.3)	(−6.3)		
Driving range on full battery (excluded category is 75 miles)				
150 miles	0.83	0.44	$5322	$71
	(3.9)	(5.0)		
200 miles	0.89	0.84	$8333	$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 h)				
5 h	0.58	0.09	$2194	$434
	(2.7)	(1.2)		
1 h	1.05	0.45	$5972	$945
	(5.3)	(5.7)		
10 min	1.31	0.74	$8748	$3331
	(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	$1455	$29.2
	(2.0)	(0.8)		
95% lower	0.54	0.28	$3466	$101
	(2.8)	(3.2)		
Acceleration relative to preferred GV (excluded category is 20% slower)				
5% slower	0.58	0.06	$1932	$129
	(2.7)	(0.7)		
5% faster	0.91	0.28	$4452	$252
	(4.1)	(3.2)		
20% faster	1.2	0.50	$6631	$145
	(5.3)	(5.6)		
Log likelihood	−9459.7			
Sample size	12,116			

converged but included a class with less than one percent membership and with standard errors orders of magnitude larger than the parameter estimates. Examining the parameter estimates for the two-class model, one class was easily identified as EV-oriented and the other as GV-oriented.

5.3. Class membership model parameters

The class membership model is shown in Table 4. The parameter estimates are close to the results from Hidrue et al. (2011). Given our survey design, this was expected. Since the results are nearly the same as in our earlier paper, we will keep the discussion brief.

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 4. 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 Hybrid indicates that a person whose preferred GV 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 being 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.

5.4. The vehicle choice model parameters

The parameter estimates for the C-EV attributes (β_x) and the V2G attributes (β_y) were estimated simultaneously. The parameters for the C-EV attributes are very close to the results from Hidrue et al. (2011) and we will not discuss these here. However, for comparison, we have reported them in Table 5. Our interest in this paper is on the V2G-EV attributes, which are reported in Table 6. 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.

We present multinomial logit (MNL) results along with our latent class (LC) results in Table 6. Comparing these shows the advantage of the LC over the MNL Model. The LC Model provides a statistically better fit and reveals significant preference heterogeneity in the data.

Looking at the sign of the parameters, we see most of them work as expected. 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. Respondents dislike high RPT and low GMR—utility decreases as required plug-in time increases and as the minimum guaranteed driving range decreases. All this is reasonable.

Comparing the parameter estimates between the two classes of the LC model reveals preference heterogeneity in the population. For example, the V2G-EV constants show a clear split in the classes. The V2G-EV

Table 6
Parameter estimates and implicit prices for the V2G-EV portion of the latent class RUM model (t-statistics in parenthesis).

Attributes	MNL model[a]	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	$1529[b]	−$2125	−$497[b]
	(−0.9)	(1.4)	(−2.35)			
75 miles	−0.29	−0.37	−0.44	−$2176[b]	−$5500	−$4020
	(−5.1)	(−1.91)	(−6.03)			
25 miles	−0.66	−1.13	−0.79	−$6.647	−$9875	−$8438
	(−9.0)	(−3.8)	(−9.3)			
RPT = length of required plug-in time per day (excluded category is 5 h):						
10 h	−0.11	0.07	−0.23	$412[b]	−$2875	−$1411[b]
	(−2.0)	(0.36)	(−3.1)			
15 h	−0.32	−0.43	−0.48	−$2529	−$6000	−$4454
	(−5.7)	(−2.1)	(−6.3)			
20 h	−0.63	−1.42	−0.69	−$8353	−$8625	−$8504
	(−9.8)	(−5.5)	(−8.9)			
Log likelihood value	−10,938.8	−9472				
Sample size[c]	12,064	12,116				

[a] The MNL Model includes the same set of individual-characteristic variables used in the class membership stage of the LC Model (see Table 4). These variables enter as interactions on the V2G constant in the MNL Model. Since we have opted for the LC Model in our final analysis, we have excluded these interactive coefficient estimates to keep the table compact.
[b] Based on a statistically insignificant parameter at the 5% level of confidence.
[c] The data has missing demographic information for 13 people. In estimating the models, these observations were dropped from the MNL Model. The RUM part of the LC model does not have demographic variables and is estimated on the full dataset.

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.

We also see preference heterogeneity for the other parameters. However, when the signs are the same, direct comparison of the parameters is difficult, since the two classes have different scale parameters. Calculating implicit prices eliminates the scale difference and allows direct comparison. We present the implicit prices in the last three columns of Table 6. The implicit prices for each class are estimated by dividing the negative of 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 for each person—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, the two classes 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 at 25 miles and RPT is at 20 h/day.

Respondents in the two classes also 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. However, it is important to note that both classes discount cash back heavily. Following Train (1985), we estimated the implicit discount rate consumers used when they make their choice. Assuming 10 years of life span for the V2G vehicle, we found consumers in the EV-class used a discount rate of 41% while those in the GV-class used 56%. The probability weighted discount rate for the entire sample is 53.5%. Increasing the life span of the vehicle has only a marginal effect on the discount rate.

While it is well documented that consumers heavily discount investment in energy conservation (see for example Train (1985) and Hausman (1979)), our estimates are on the higher end. For example, recent studies that examined consumer choice of hybrid and alternative fuel vehicles found discount rates in the range of 20% to 25% (Horne et al., 2005; Mau et al., 2008; Axsen et al., 2009). However, the high discount rate in our data may be plausible given the unfamiliarity of the V2G technology and the high initial cost it involves. Howarth and Sanstad (1995) argue that high implicit discount rates might reflect a perceived risk of energy efficient investments. Hassett and Metcalf (1993) argue that high discount rates are rational rates if future savings are highly uncertain. The high discount rate may also reflect respondents' mistrust of power companies as some people indicated in our focus groups.

The weighted implicit prices in Table 6 show that respondents see a high inconvenience with GMR and RPT over ranges actually being considered for policy. People, it seem, place a high value on flexibility in their driving lifestyles. Reducing GMR from 175 to 125 has the same negative effect on consumers as increasing the initial price of the car by $497. Not much. But, reducing it from 175 miles to 75 miles is equivalent to increasing the initial price by $4020, and reducing it from 175 to 25 miles is equivalent to an $8438 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 h per day—a rather short period of required plug-in time. On average, increasing RPT from 5 h to 10 h is equivalent to increasing initial price by $1411. Increasing it further to 15 h and 20 h is equivalent to increasing initial price by $4454 and

Table 7
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 h	$2368	$4252
B	75 miles	10 h	3052	5875
C	75 miles	15 h	4419	8741
D	75 miles	20 h	6480	12,758
E	25 miles	5 h	4511	8668
F	25 miles	10 h	5195	10,292
G	25 miles	15 h	6562	13,157
H	25 miles	20 h	8622	16,628

$8504. The per-hour incremental costs are $282/h (5 to 10 h), $608/h (10 to 15h), and $810/h (15 to 20 h).

We find the RPT coefficients surprisingly high given that the average car is idle about 23 h/day. In the survey, we asked respondent to consider the potential availability of plug-in options at work (e.g. for hospital workers or university employees this might make sense, for farmers or small business owners it might not). If respondents considered the likelihood of this for their own circumstance, the range of RPTs should not have been viewed as constraining for many people. Nevertheless, respondents did not appear to treat RPT as simple use of idle vehicle time; rather they seemed to focus on its potential for inconvenience. We observed the same in focus groups even after describing the length of time available to most for plugging in.

6. Can the V2G concept help sell EVs?

In this section we use our model to evaluate 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 power provided to the grid, they could make EVs more 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 enter the market. We do not attempt to estimate potential market share for V2Gs explicitly, since that seems beyond the reach or our data, but we can say some about willingness to pay relative to cost and that does has implications for success or failure 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 of 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 compensation (*MCBC*) required to compensate a person for RPT and GMR inconvenience in our model is the value of *MCBC* that solves the following equation

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

where the left-hand side is the utility for a C-EV, the right-hand side is the utility for a V2G-EV. 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

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

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

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

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 (*MPR*) is the value of *MPR* that solves

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

In this case the compensatory value is an asset value since it is calculated using the price of the car. A weighted measure, MPR_w, is derived in the same way as $MCBC_w$ is derived.

Our calculation of $MCBC_w$ and MPR_w for several V2G scenarios is shown in Table 7. The contracts were constructed using *RPT* (=5, 10, 15 and 20 h) 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 of driving range.

The estimated minimum required compensation for each contract is shown using a Box–Whisker Plot in Fig. 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 annually minimum required contract prices over the sample. The median required compensation ranges from a low of near $2368 for Contract A (GMR = 75 & RPT = 5) to a high of near $8622 for Contract H (GMR = 25 & RPT = 20). Again, see Table 7 for both contracts. The question then is whether or not these amounts, especially those at the minimums in Fig. 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 (different regions have different A/S prices), power capacity of the connection, hours connected, and so forth. We used a study by Kempton and Tomić (2005) to assess the

[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.

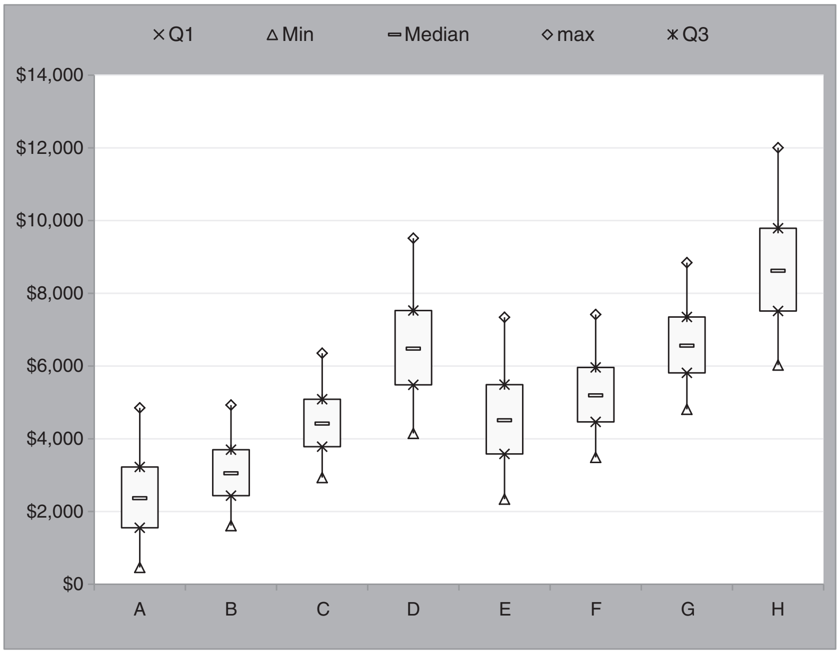

Fig. 3. Box–Whisker plot based for minimum required annual compensation in cash-back terms for eight contracts (A through H) listed in Table 7. The range of required compensation payments is due to the variation (heterogeneity) over the sample.

feasibility of attaining our estimated earnings requirements. They estimated the potential net revenue a Toyota RAV4 EV can earn with a V2G contract of RPT = 18 h and GMR = 20 miles. 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 $2554 annually (close to $2900 in 2009 dollars). Our Fig. 3 shows that the minimum required contract payments for a similarly configured contract (GMR = 25 & RPT = 20) are near $8000. Making roughly the same calculations for the other scenarios has little effect on the story. If the Kempton and Tomić (2005) values are correct, V2G would not help EVs enter the market because its perceived cost in inconvenience is greater than the total value of the value to the grid. 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 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.

We suggest two other approaches for V2G payments. First, V2G payments could be made as up-front price discounts on V2G vehicles since respondents were shown to heavily discount annual cash-back payments. Fig. 4 shows the same Box–Whisker Plot for an up-front

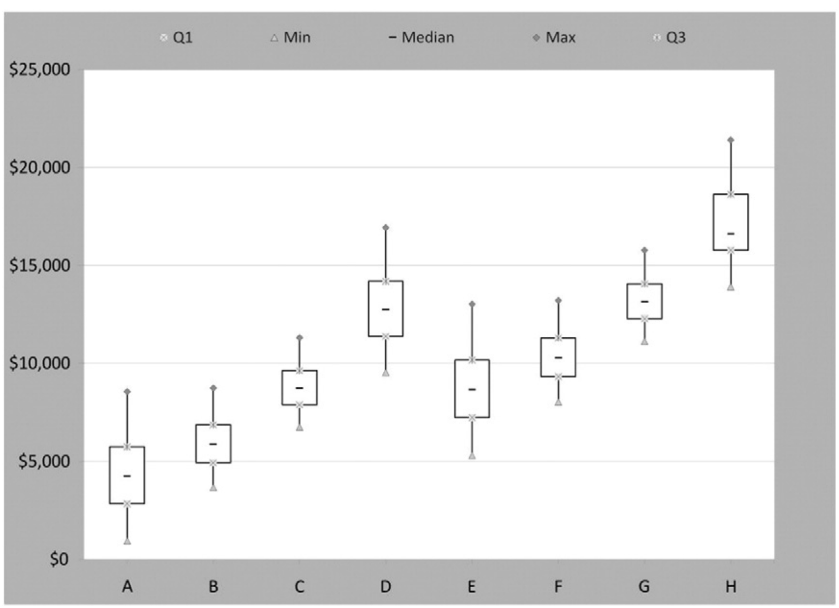

Fig. 4. Box–Whisker plot for upfront discounts on purchase of vehicle for eight contracts (A through H) listed in Table 7. The range of required compensation payments is due to the variation (heterogeneity) over the sample.

cash discount. These are calculated using Eq. (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 aggregator's money, gives $2190. This should be low enough to bring some drivers 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 or pay-as-you-go 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.[4] One difficulty is the uncertainty it 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 the level of back-up power they can supply to the market. 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 accordingly. 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 others use pay-as-you-go.

7. 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 that 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 suggest two strategies as alternatives to the strict cash-back-contract approach. 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 to bring respondents along slowly as they learned the material and were forced to evaluate options stepwise in the two simpler experiments. In focus groups, we found that the stepwise approach improved comprehension.

[4] One system uses predictions and scheduling based on historic consumer behavior to insure against inconveniences (US Patent and Trademark Office, 2010).

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