Do battery-switching systems accelerate the adoption of electric vehicles? A stated preference study

Ito, Nobuyuki

Takeuchi, Kenji

Managi, Shunsuke

(Citation)
Economic Analysis and Policy,61:85-92

(Issue Date)
2019-03

(Resource Type)
journal article

(Version)
Accepted Manuscript

Do Battery-Switching Systems Accelerate the Adoption of Electric Vehicles? A Stated Preference Study

Nobuyuki Ito[†], Kenji Takeuchi[¶], and Shunsuke Managi[‡]

[†] *Center for the Promotion of Interdisciplinary Education and Research, Kyoto University, Japan*
nobuyuki.itoh@gmail.com

[¶] *Graduate School of Economics, Kobe University, Japan* takeuchi@econ.kobe-u.ac.jp

[‡] *Urban Institute & School of Engineering, Kyushu University, Japan* managi.s@gmail.com

Abstract

We estimate willingness-to-pay (WTP) for battery-switching electric vehicles (SEVs) by using a stated choice experiment. Our estimation results show that individuals have high WTP for SEVs, provided sufficient battery-switching stations exist. When battery-switching infrastructure represents 50% of the current number of gasoline stations, individuals are indifferent between conventional gasoline vehicles and SEVs, which have a 521 thousand yen lower price than gasoline vehicles. Moreover, the estimation results suggest that vehicle drivers may recognize SEVs as vehicles for shorter drives such as daily shopping trips and thereby have lower marginal WTP with respect to cruising range.

JEL Classification: L62, Q42, Q51

Keywords: electric vehicle, battery-switching stations, stated preference method, choice experiment, willingness-to-pay

1 Introduction

Electric vehicles (EVs) are expected to play a significant role in reducing carbon emissions from the transportation sector. More than 550 thousand EVs were sold worldwide in 2015, increasing the global inventory of EVs to 1.26 million (Electric Vehicles Initiative, 2016). While these figures are promising, EVs still represent only 0.1% of all passenger cars globally. One of the major obstacles to the further adoption of EVs might be consumer anxiety about the technology. EVs have a lower driving range compared with conventional gasoline vehicles (GVs) and require a longer time for fuel charging.

One solution to this problem might be investment in battery-switching systems for EVs. An EV battery-switching station allows drivers to exchange their depleted battery for a fully charged one in just a few minutes. Since the driver does not own the battery in the car and is charged per mile driven, it is also possible to reduce the upfront costs that prevent people from purchasing EVs. However, the notion of battery switching has been unsuccessful so far. Better Place, a venture company that developed battery-switching services for EVs, and attracted significant attention and capital, collapsed in May 2013 (Pearson and Stub, 2013). Tesla Motors presented the idea of battery swap stations in June 2013, but is unlikely to pursue further development at present (Korosec, 2015).

This study investigates potential demand for battery-switching EVs (SEVs) by using a stated preference survey. Since demand for alternative fuel vehicles critically depends on the availability of fuel charging stations (Ito et al., 2013), it is important to incorporate this feature into any analysis of demand for EVs. The choice experiment design used in this study allows us to investigate whether consumers evaluate SEVs differently from REVs. More specifically, the effect of fuel availability on willingness to buy EVs might be different between these two types of EVs. WTP for SEVs could be strongly affected by the availability of switching stations, since the attractiveness of switchable batteries critically depends on the infrastructure network specially designed for this technology.

Several studies have investigated the potential demand for EVs by using a stated preference methodology (Beggs et al., 1981; Ewing and Sarigöllü, 1998; Bunch et al., 1993; Brownstone et al., 2000; Axsen et al., 2013; Ito et al., 2013). These studies ask respondents, using hypothetical questions, to choose their preferred alternative from a set of profiles that have different levels of car attributes. From the estimated coefficients of these attributes, the marginal WTP for attributes of EVs can be calculated. Many previous studies have focused on the driving range of EVs. For example, Daziano (2013) found that the mean estimated WTP for a one-mile improvement in the driving range of an EV in the past studies in the United States was 100 dollars per mile. Infrastructure development for EVs has been of less focus in previous studies even though consumer evaluation of driving range may be sensitive to the availability of refueling infrastructure (Dimitropoulos et al. 2013). Moreover, to our knowledge, no study has thus far examined the difference in WTP for SEVs and REVs.

The rest of the paper is organized as follows. Section 2 introduces the survey design of our stated preference questionnaire. Section 3 explains the empirical strategy for the WTP estimation. Section 4 presents the estimation results and their implications. Section 5 concludes.

2 Survey design

2.1 Vehicle attributes and their levels

The decision to purchase a car depends on various factors. In this study, we select nine attributes based on our research objectives and the findings of previous studies. While the number of attributes is large, these are typical attributes that consumers consider when they purchase automobiles.[1] Attributes connected with refueling, refueling rate, and fuel availability are important factors that affect vehicle choice (Ewing and Sarigöllü, 1998; Potoglou and Kanaroglou, 2007). Table 1 presents the attributes and their levels used in our study. The levels of each attribute are correlated with the fuel types because of their technological characteristics. Details of the attributes can be summarized as follows.

Fuel type: To investigate potential demand for SEVs relative to other vehicles that use different types of fuel, we considered the following four fuel types: GVs, hybrid electric vehicles (HEVs), REVs, and SEVs. GVs were treated as the base alternative that respondents were willing to purchase.

// Table 1: The attributes and levels of the choice experiment //

Body type: Respondents were asked to choose the best and the second-best vehicle body type that they would consider in their next purchase decision out of nine alternatives; these two body types were used to create respondent profiles. The following nine alternatives of vehicle body type were included in the choice experiment: subcompact, compact/hatchback, coupe, sedan, convertible, wagon, minivan,

[1] In the survey, we asked respondents if they made their choice with confidence. Only a fraction of respondents (14%) answered no to this question. Therefore, we believe that most of the respondents understood and answered the choice tasks appropriately.

SUV/pickup truck, and truck/bus. The body types are assumed to be unrelated to fuel type. In the estimation model, we include dummy variables for coupe, sedan, wagon, minivan, and SUV/pickup truck, using the other body types as a base category.

Manufacturer: Respondents were asked to choose one automobile manufacturer that they would consider in their next purchase decision from a list of 32 manufacturers. The list of 32 manufacturers included foreign companies (those not headquartered in Japan). We used the respondent choices to create profiles for the base alternative. It was assumed that only the following four representative automobile manufacturers in Japan produce HEVs, REVs, and SEVs: Toyota Motor Corporation, Honda Motor Company, Nissan Motor Company, and Mitsubishi Motors Corporation. In the estimation model, we include dummy variables for Toyota, Honda, Nissan, Mitsubishi and foreign manufacturers, using other manufacturers as the base category.

Cruising range: Cruising range is a critical attribute for choosing alternative fuel vehicles. Cruising ranges were set as 800 kilometers for GVs; between 800 kilometers and 1,200 kilometers for HEVs; and between 100 kilometers and 300 kilometers for REVs and SEVs.[2]

Refueling rate: The total time for refueling was set as 5 minutes, except for REVs. Compared with other vehicles, REVs usually take a longer time to recharge. It takes 30 minutes to recharge the battery of REVs at a fast-charging station. We use 10, 15, and 30 minutes as the refueling rates, considering the potential technological development. When battery-switching stations are available for SEVs, the time to recharge is less than 5 minutes. For example, Tesla Motors announced that it takes only 90 seconds to switch

[2] The cruising range of Nissan's EV model Leaf is up to 107 miles (172.2 km) on every charge (https://www.nissanusa.com/electric-cars/leaf/charging-range/range/).

batteries for EVs.[3] Respondents watched a few minutes of video that introduced how a driver can switch the discharged battery for a fully charged one in an SEV at a battery-switching station.

Carbon dioxide emissions: It was assumed that by choosing HEVs or EVs, drivers can reduce their car emissions of carbon dioxide. When a respondent chooses an HEV, his or her car emission levels of carbon dioxide are reduced by 50% at most from current levels of emissions from GVs. When a respondent chooses REVs or SEVs, car emissions are reduced by 80% at most from current GV levels.

Fuel availability: Fuel availability was described in terms of a percentage of refueling stations at existing gasoline stations. Thus, the fuel availability for GVs and HEVs was 100%. The fuel availability for REVs and SEVs were lower than GVs (10–75%). In Japan, there were more than 13,000 places where a fast-charging service for EVs was available as of October 2016[4] and 32,000 gasoline stations as of March 2015.[5]

Purchase price: The purchase price for GVs was based on respondents' answers regarding the amount they would spend on their next vehicle purchase. The purchase prices for HEVs, REVs, and SEVs were calculated based on a certain increase over the price customers would pay for GVs.

Annual fuel cost: The annual fuel costs for GVs were calculated from respondents' current number of refuels per month and the average amount they spend per refuel. The annual fuel costs for HEVs, REVs, and SEVs were calculated by a certain decrease in annual fuel costs from GVs. Respondents were instructed to assume that the annual fuel costs of REVs included the cost of replacing the batteries.

[3] https://www.tesla.com/jp/videos/battery-swap-event
[4] The data are from CHAdeMo. http://www.chademo.com/wp/
[5] http://www.meti.go.jp/press/2016/07/20160712003/20160712003.html

Respondents were also instructed to assume that all the other attributes not indicated in the choice set were identical among the alternatives. Respondents were able to obtain information regarding the above vehicle attributes by clicking a link while answering the choice experiment questions.

2.2 Design of choice sets

The number of alternatives in each choice set was set as three. An example of a choice set is presented in Figure 1. The profile for vehicle 1 (GVs) was created on the basis of respondents' answers regarding their next purchase opportunity. Throughout the eight choice sets that each respondent faced, vehicle 1 was fixed as the base alternative.

The profiles for HEVs, REVs, and SEVs were created by using orthogonal arrays for 10 attributes and four levels. In total, 64 profiles for each alternative fuel vehicle were constructed; therefore, 192 (64 × 3) profiles of alternative fuel vehicles were compiled. The profiles of GVs were the same between choice sets. Then, two profiles from the alternative fuel vehicles were randomly drawn and matched with the GV profile; hence, 128 choice sets and 16 versions of a series of eight choice sets were created. One of the 16 versions was randomly assigned to each respondent.

// Figure 1: Example of a choice set //

2.3 Data

We conducted a web-based survey between February 21 and 25, 2011. The clarity of the questionnaire was checked by a pretest conducted in December 2010. We sent e-mails to invite 53,066 individuals registered to the online survey, ages 19 to 69. The response rate was 14.15%. Among these 7,511 responses, we used data for 2,408 respondents who had a driver's license and planned to purchase a car in the future. Table 2 reports the summary statistics.

// Table 2: Summary statistics of respondent characteristics //

3 Random utility model

We apply a random utility model to estimate preference parameters of attributes describing properties of vehicles. In the estimation, we use a random parameter logit model, which allows for preference heterogeneity among respondents and their unrestricted substitution patterns (McFadden and Train, 2000). The utility of respondent *n* obtained from alternative *j* in choice situation *t* is defined as

$$U_{njt} = \beta_n' x_{njt} + \varepsilon_{njt} \tag{1}$$

where β_n denotes the vector of the random coefficients and x_{njt} denotes the vector of attribute levels of alternative *j* in choice situation *t*, and ε_{njt} denotes the unobserved utility, which is an independently and identically distributed Gumbel distribution. We assume that β_n follows normal distribution and estimate the means and variances of the distributions.

Suppose that β_n is known, and the probability that a series of choices y_n made by respondent *n* is observed and given by

$$\Pr(y_n \mid x_n, \beta_n) = \prod_t \frac{\exp(\beta_n' x_{ny_{nt}t})}{\sum_j \exp(\beta_n' x_{njt})} \tag{2}$$

where y_{nt} denotes the alternative, which respondent n chooses in situation t; and, y_{nt} can vary depending on choice situations. Since β_n is the vector of the random coefficients and we do not know β_n but we know the means and variances, the probability that respondent n makes a series of choices over the distribution of β is given as:

$$\Pr(y_n \mid x_n, \theta) = \int \Pr(y_n \mid x_n, \beta) g(\beta \mid \theta) d\beta \tag{3}$$

where θ denotes the parameters of the means and covariances of β and g denotes the density of β. In the estimation, we used maximum simulated likelihood estimation.

4 Estimation results

4.1 Main results

The estimation results of the random parameter logit model are shown in Table 3. The explanatory variables that have standard deviations are the variables having random coefficients and those that do not have them are variables having nonrandom coefficients. We include the quadratic terms for cruising ranges and establishment of infrastructure in the model to capture the diminishing effect of these factors on vehicle choice. The estimated results for the coefficients of the explanatory variables used in our models are as follows.

Alternative specific constants (ASCs): There are five ASCs in our model: HEVs, REVs with three different refueling rates, and SEVs. We use vehicle 1 (GVs) as a base category. All ASCs are positive and statistically significant. This indicates that a consumer prefers alternative fuel vehicles to GVs provided that all other vehicle attributes are the same. The difference between the means of the coefficients of REVs with recharging rates of 30 and 10 minutes indicates that reducing the time required for recharging at a station increases consumers' utility. The standard deviations of the coefficients of REVs with recharging rates of 10 and 30 minutes are not significant, indicating that there is no heterogeneous preference for the recharging rate.

Fuel availability: The mean of the coefficient of *Station* is positive, whereas that of *Station* squared is negative. These results are consistent with our expectations that the marginal utility of expanding stations for refueling diminishes. The mean of the coefficient of the interaction term between SEVs and *Station* is positive but statistically insignificant. This means that the marginal benefit of expanding stations for SEVs is similar to that for other vehicles. All the standard deviations of the coefficients of the terms of *Station* are significant, indicating that there are heterogeneous preferences among consumers for fuel availability.

Cruising range: The coefficient of cruising range and its squared term represent the marginal utilities in the utility function. As expected, the mean of the coefficient of cruising range is positive and the squared term is negative. These results indicate that marginal utility of a longer cruising range diminishes. We also estimated the parameters of the cross terms between REVs and SEVs and the square term of the cruising range. The means of coefficients of these cross terms are negative, which means that the marginal WTP for the cruising range of REVs or SEVs is lower than that for HEVs. Note that the cruising range of HEVs is different than in EVs. The standard deviation of the coefficient of the interaction term of *Range* and EVs is not significant, indicating that there is no preference heterogeneity for the cruising range of REVs or SEVs.

Carbon dioxide emissions: The mean of the coefficient for reduction of carbon dioxide emissions is significantly positive, indicating that emission reduction significantly increases consumers' utility.

Body types: We include dummy variables for coupe, sedan, minivan, wagon, and SUV/pickup truck in the estimation model. The base category for these dummy variables is other body types. The means of the coefficients of the sedan and the wagon are negative, whereas the coefficients of the coupe, SUV/pickup truck, and minivan are not statistically significant. These results indicate that the WTP for HEVs, REVs, and SEVs decreases when the body type is either a sedan or a wagon compared to other body types.

Manufacturers: We include dummy variables for Toyota, Honda, Nissan, Mitsubishi, and foreign manufacturers, using other manufactures as the base category. The coefficients of Toyota and Honda are positive and statistically significant. The means of the coefficients of Nissan, Mitsubishi, and foreign manufacturers are not statistically significant. These results indicate that although WTP for HEVs, REVs, and SEVs increases when the manufacturers are Toyota and Honda, there is no difference in WTP among Nissan, Mitsubishi, foreign manufacturers, and others.

// Table 3: Estimation results of random parameter logit model //

4.2 Establishment of infrastructure

The estimated mean coefficients suggest that infrastructure development for EVs is positively evaluated by respondents. We can calculate the WTP for establishing refueling stations by using the population mean coefficients of *Station*. The WTP for expanding recharging stations for REVs to a certain percentage of the current number of gasoline stations can be calculated by

$$WTP^{REV}_{Station} = -\frac{\mu_S Station + \mu_{S2} Station^2}{\beta_p} \tag{4}$$

where μ_S is the population mean of the random coefficient for *Station*, μ_{S2} is that for *Station* squared, and β_p is the nonrandom coefficient for *Price*.

The WTP for expanding battery-switching stations for SEVs can be calculated by

$$WTP^{SEV}_{Station} = -\frac{(\mu_S + \gamma_{SEV}) Station + \mu_{S2} Station^2}{\beta_p} \tag{5}$$

where γ_{SEV} is the population mean of the random coefficient of the interaction term between *SEV* and *Station*. Note that because the mean of the random coefficient of the interaction term between SEV and Station is not statistically significant, we can interpret that the population mean of the WTP for establishing refueling stations for SEV is also equal to that for REV. Moreover, there are heterogeneous preferences for the difference in the WTP for establishing refueling stations between SEV and REV.

Figure 2 shows WTP to build infrastructure for REVs and SEVs in terms of a percentage of current gasoline stations on the horizontal axis. For example, WTP to for REV and SEV infrastructure in as many as 50% of the current gasoline stations is about

6,660 US dollars and 7,510 US dollars, respectively. Under a plausible scenario,[6] the price of the SEV would need to be 2,220 US dollars lower than the GV to make the SEV an indifferent choice for consumers.

Figure 2 also shows that although the WTP for improving infrastructure for REV and SEV continues to increase up to 75% of the current gasoline stations, which is the maximum of the attribute levels, the marginal WTP for refueling stations, which is defined as the WTP for an extra 1% of the stations built, decreases as the number of the stations increases.

// Figure 2: WTP to build the infrastructure of REVs and SEVs //

Figure 3 shows the choice probabilities of EVs for various price differences between EVs and GVs. Choice probabilities of EVs are small, even though there are many refueling stations. For example, the choice probability of the SEV is less than 0.1, even when battery-switching stations are built for as many as 75% of the current gas stations. The results also indicate that the impact of infrastructure improvement on choice probabilities of EVs is larger as the price difference decreases. Furthermore, assuming that the number of refueling stations is equal between REVs and SEVs, choice probabilities of REVs with a refueling rate of 30 minutes are higher than those of SEVs at the given levels of infrastructure. These results imply that to promote the use of EVs, it is important to improve infrastructure and introduce a price subsidy that makes EVs preferable.

[6] We assume that the cruising range and the number of stations of GVs are 800 kilometers and 100%, respectively, and the emission reduction level of GVs and EVs are 0% and 50%, respectively.

// **Figure 3: Choice probabilities of EVs and levels of refueling stations** //

4.3 Cruising range of EVs

The WTP for the cruising range of HEVs and EVs can also be defined as

$$WTP_{Range}^{HEV} = -\frac{\mu_R Range + \mu_{R2} Range^2}{\beta_p} \tag{6}$$

and

$$WTP_{Range}^{EV} = -\frac{(\mu_R + \gamma_{EV}) Range + \mu_{R2} Range^2}{\beta_p}, \tag{7}$$

respectively, where μ_R, μ_{R2}, and γ_{EV} denote the population mean coefficients of *Range* and *Range* squared, and the interaction term of *Range* and the sum of dummy variables of all the *REV*s and *SEVs* (i.e., the term is zero if the fuel type is other than EV). Figure 4 shows the WTP for the cruising range of alternative fuel vehicles. Similar to the relationship between the WTP and refueling stations, marginal WTP diminishes with respect to cruising range.

The WTP for a cruising range of 200 kilometers for either REVs or SEVs is about 6,600 US dollars. The marginal WTP for a cruising range of a HEV at 300 kilometers, which is defined as the WTP for an extra one kilometer of *Range*, is 53.6 US dollars and greater than for an EV at 300 kilometers (18.6 US dollars). The results suggest that drivers may see REVs and SEVs as vehicles for shorter drives such as daily shopping trips.

// Figure 4: WTP for cruising range //

5 Concluding Remarks

Notwithstanding their expected role in reducing carbon dioxide emissions for mitigating climate change, the current penetration of EVs is still very low. Battery-switching systems could significantly promote EV use by alleviating driving range anxiety and reducing the upfront cost of purchase. However, based on our hypothetical scenarios, our results indicate that even with a REV refueling rate of 30 minutes, choice probabilities of the REV are higher than those of the SEV under equal accessibility of refueling stations. To make consumes indifferent between the SEC and a GV, the price of the SEV must be 2,220 US dollars lower than the GV. Moreover, the impact of infrastructure improvement on choice probabilities of EVs increases as the price difference between EVs and GVs decreases. This implies that to promote the use of EVs, it is important to improve infrastructure and concurrently introduce a price policy that makes EVs more attractive.

The price of batteries might be different in the future. For example, the estimated cost of Li-ion battery packs for EV manufacturers have declined by approximately 14% annually (Nykvist and Nilsson, 2015). The bankruptcy of Better Place and the retreat of Tesla Motors from battery-switching systems are evidence of the difficulty of developing a network of battery-switching stations in a profitable manner. Maintaining such a system is costly, as it requires more batteries than the number of EVs on the road (Avci et al., 2015). On the other hand, there is an ancillary benefit of a battery-switching system such as avoiding high peak demand and the ability to coordinate discharging back to the power grid through vehicle-to-grid technology

(Widrick et al., 2016). The consideration of these costs and benefits are necessary to appropriately judge the economic rationality of adopting battery-switching systems for EVs in the future.

Acknowledgement

This study was supported by a grant from the Policy Studies of the Environment and Economy (years 2009–2011) and S15 of the Ministry of Environment, Japan, and JSPS KAKENHI Grant Numbers JP16H03006, JP26241033, and JP26000001.

References

Avci, B., Girot, K., Netessine, S., 2015. Electric vehicles with a battery switching station: adoption and environmental impact. Management Science 61 (4), 772–794.

Axsen, J., Orlebar, C., Skippon, S., 2013. Social influence and consumer preference formation for pro-environmental technology: the case of a U.K. workplace electric-vehicle study. Ecological Economics 95, 96–107.

Beggs, S., Cardell, S., Hausman, J., 1981. Assessing the potential demand for electric cars. Journal of Econometrics 17 (1), 1–19.

Brownstone, D., Bunch, D.S., Train, K., 2000. Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles. Transportation Research Part B 34, 315–338.

Bunch, D.S., Bradley, M., Golob, T.F., Kitamura, R., Occhiuzzo, G.P., 1993. Demand for clean-fuel vehicles in California: a discrete choice stated preference pilot project. Transportation Research Part A 27 (3), 237–253.

Daziano, R., 2013. Conditional-logit Bayes estimators for consumer valuation of electric vehicle driving range. Resource and Energy Economics 35, 429–450.

Dimitropoulos, A., Rietveld, P., van Ommeren, J.N., 2013. Consumer valuation of changes in driving range: a meta-analysis. Transportation Research Part A: Policy and Practice 55, 27–45.

Electric Vehicles Initiative, 2016. Global EV Outlook 2016. OECD/IEA.

Ewing, G.O., Sarigöllü, E., 1998. Car fuel-type choice under travel demand management and economic incentives. Transportation Research Part D: Transport and Environment 3 (6), 429–444.

Ito, N., Takeuchi, K., Managi, S., 2013. Willingness to pay for infrastructure investments for alternative fuel vehicles. Transportation Research Part D: Transport and Environment 18, 1–8.

Korosec, K., 2015. Tesla's battery swap program is pretty much dead. Fortune (June 10), http://fortune.com/2015/06/10/teslas-battery-swap-is-dead/.

McFadden, D., 1974. Conditional logit analysis of qualitative choice behavior. In P. Zarembka (ed.), Frontiers in econometrics, 105–142, Academic Press: New York.

McFadden, D., Train, K. 2000. Mixed MNL models for discrete response. Journal of Applied Econometrics 15 (5), 447-470.

Nykvist, B., Nilsson, M. 2015. Rapidly falling costs of battery packs for electric vehicles. Nature Climate Change 5, 329–332.

Pearson, D., Stub, S.T., 2013. Better Place's failure is blow to Renault. Wall Street Journal (May 29), http://online.wsj.com/articles/SB10001424127887323855804578507263247107312.

Potoglou, D., Kanaroglou, P.S., 2007. Household demand and willingness to pay for clean vehicles. Transportation Research Part D: Transport and Environment 12 (4), 264–274.

Widrick, R.S., Nurre, S.G., Robbins, M.J., 2016. Optimal policies for an EV battery swap station. Transportation Science, Articles in Advance, 1–21.

Table 1: The attributes and levels of the choice experiments

Attributes		**Levels**			
Fuel type		GV	HEV	REV	SEV
Body type	GV	Base 1a			
	HEV/REV/SEV	Base 1a	Base 1b		
Manufacturer	GV	Base 2a			
	HEV/REV/SEV	Base 2a	Base 2b		
Cruising range (km)	GV	800			
	HEV	800	900	1000	1200
	REV/SEV	100	150	200	300
Refueling rate (minutes)	GV/HEV/SEV	5			
	REV	10	15	30	
Fuel availability (% of the existing gasoline stations)	GV/HEV	100%			
	REV/SEV	10%	25%	50%	75%
Carbon dioxide (% reduction from present car average)	GV	0%			
	HEV	20%	30%	40%	50%
	REV/SEV	50%	60%	70%	80%
Purchase price (including tax)	GV	Base 3			
	HEV	Base 3+10%	Base 3+20%	Base 3+30%	Base 3+50%
	REV	Base 3+20%	Base 3+40%	Base 3+60%	Base 3+80%
	SEV	Base 3−10%	Base 3−5%	Base 3+5%	Base 3+10%
Annual fuel cost	GV	Base 4			
	HEV	Base 4−50%	Base 4−40%	Base 4−30%	Base 4−20%
	REV	Base 4−80%	Base 4−60%	Base 4−40%	Base 4−20%
	SEV	60,000+ (Base 4−50%)	80,000+ (Base 4−80%)	100,000+ (Base 4−80%)	150,000+ (Base 4−80%)

Note: Base 1, Base 2, Base 3, and Base 4 are specified by respondents and differ among respondents. Base 1a and Base 2a are the best alternatives and Base 1b and Base 2b are the second-best alternatives.

Table 2: Summary statistics of respondent characteristics

	Mean	SD	Min	Max	N
Female	0.49	0.5	0	1	2408
Age	44.622	13.220	20	69	2408
Household income (10^4 yen)	650.416	397.456	50	2250	2165

Note: N denotes the number of respondents. The exchange rate was ¥77.57/$ as of 2011.[7]

[7] The Bank of Japan (http://www.boj.or.jp/)

Table 3: Estimation results of random parameter logit model

Explanatory variables	Mean Coeff.	Std. Err.	Std. dev. of Coeff.	Std. Err.
Alternative specific constants				
HEV	1.700 ***	0.128	0.945 ***	0.112
REV rechargeable in 10 minutes	2.837 ***	0.718	0.001	0.201
REV rechargeable in 15 minutes	2.873 ***	0.723	0.409 ***	0.139
REV rechargeable in 30 minutes	2.714 ***	0.724	0.155	0.359
SEV	2.195 ***	0.729	1.791 ***	0.086
Vehicle attributes				
Range [100 km]	0.761 ***	0.180	0.221 ***	0.011
Range^2 [10,000 km]	−0.033 ***	0.009	0.003 **	0.001
Station [%]	0.019 ***	0.005	0.006 **	0.003
Station^2 [%/1000]	−0.102 ***	0.053	0.176 ***	0.013
Emission reduction [%]	0.010 ***	0.002	0.038 ***	0.001
Price [million yen]	−1.356 ***	0.053		
Annual cost [yen]	−1.496 ***	0.082	1.587 ***	0.135
(REV+SEV)*Range^2 [10,000 km]	−0.061 *	0.034	0.006	0.018
SEV*Station [%]	0.002	0.002	0.007 ***	0.003
Body type				
Coupe	−0.117	0.101		
Sedan	−0.161 **	0.063		
SUV	0.027	0.196		
Minivan	0.016	0.199		
Wagon	−0.145 **	0.073		
Manufacturer				
Toyota	0.121 *	0.062		
Honda	0.134 *	0.069		
Nissan	0.002	0.074		
Mitsubishi	0.044	0.145		
Foreign	0.134	0.097		
Psuedo-R^2		0.319		
Log Likelihood		−16225.0		
Observation		21672		
Number of respondents		2408		

Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1: Example of a choice set

	Vehicle 1	Vehicle 2	Vehicle 3
Fuel type	Gasoline	Battery-Recharging EV	Battery-Switching EV
Body type	SUV, Pickup	SUV, Pickup	SUV, Pickup
Manufacturer	Toyota	Toyota	BMW
Cruising range	800 km	200 km	200 km
Refueling rate	5 minutes	15 minutes	15 minutes
Fuel availability	All existing service stations	75% of existing service stations	50% of existing service stations
Carbon dioxide	Present level	60% less	70% less
Purchase price	5 million yen	7 million yen	5.5 million yen
Annual fuel cost	100 thousand yen	80 thousand yen	170 thousand yen
Choose one vehicle			

Figure 2: WTP to build the infrastructure of REVs and SEVs

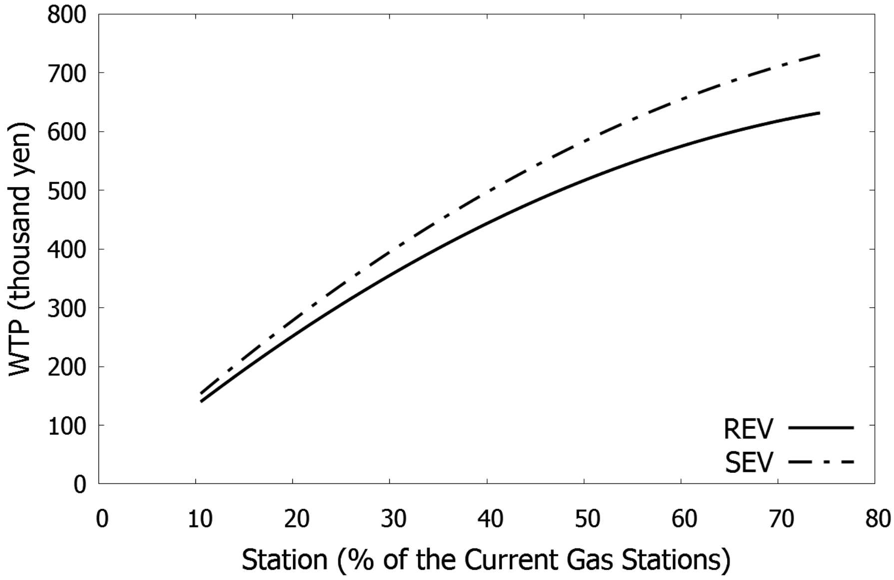
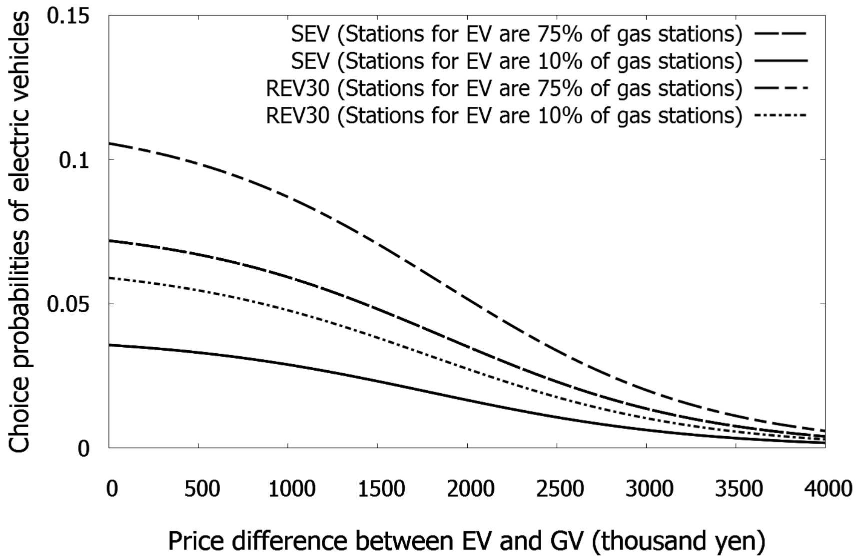


Figure 3: Choice probabilities of EVs and levels of refueling stations



Note: The simulation is based on assumptions that the price of a GV is 30 thousand US dollars; the cruising ranges of HEV and EVs are 1,200 and 200 kilometers, respectively; the levels of emission reduction of HEV and EVs are 20% and 50%, respectively; the refueling rate of REV is 30 minutes, and that there is no difference in annual costs between different fuel types.

Figure 4: WTP for cruising range