THE ROLE OF GAS ANXIETY IN THE CHARGING CHOICES OF PLUG-IN HYBRID ELECTRIC VEHICLE DRIVERS

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ABSTRACT

Plug-in hybrid electric vehicles (PHEV) provide an opportunity to reduce petroleum consumption and greenhouse gas emissions without causing range anxiety. As a result, PHEV drivers are commonly assumed to be less dependent on the availability of charging infrastructure than battery electric vehicle (BEV) drivers. However there is also evidence that PHEVs plug in more often than BEVs because the owners have gas anxiety – a strong desire to avoid using gasoline. This work examines the existence of gas anxiety by analyzing the factors influencing charging decision of PHEV owners. A web-based stated preference survey was conducted and the data was analyzed using a latent class logit model. The result shows that there are two classes of decision making patterns among PHEV owners: those who value gasoline cost and recharging expenditure almost the same (class 1) and those who value gasoline cost more heavily than recharging cost (class 2). Among those in class 2, the amount of money spent on gasoline has much bigger influence on the utility of charging than the amount spent on electricity at the recharging station, which can be interpreted as a form of gas anxiety.

Key words: PHEV, recharge, gas anxiety, stated preference data

INTRODUCTION

As a non-renewable energy source imposing serious environmental and security externalities on society, petroleum's central role in our transportation system has been a focus of concern for more than 40 years. A promising approach to reduce oil dependence and environmental impacts from automotive transportation is the electrification of the vehicle powertrain, particularly when the electricity used for recharging is derived from clean sources. While significant reductions in battery costs have been achieved *(1)*, electric vehicle (EV) batteries remain expensive and have a lower energy compared with gasoline, meaning that most electric vehicles have driving ranges that are much lower than their gasoline powered equivalents. Range anxiety – the fear of the battery being fully depleted and the driver left stranded – is one of the major limitations of electric vehicles *(2)*. Combining an internal combustion engine, an electric powertrain and onboard charging equipment, plug in hybrid electric vehicles (PHEVs) can partially substitute electricity for gasoline, potentially reducing gasoline use and GHG emissions while maintaining the ability to travel long distances and refuel quickly and conveniently *(3-5)*.

Since PHEVs have an internal combustion engine, they are generally assumed to be less dependent on charging availability than battery electric vehicles (BEVs), mitigating range anxiety in PHEV drivers. However, systematic data collection on in-use charging patterns has found that PHEV users actually plug in more often than battery electric vehicles. According to the EV Project EVSE and Vehicle Usage Report 2nd Quarter 2013, the average number of charging events per day when a PHEV was driven was about 1.4. But for a BEV, it was only 1.1. This finding seems somewhat paradoxical: drivers for whom plugging in is optional tend to do so more frequently than those for whom it is mandatory. This surprising result has led to the coining of a new term – "gas anxiety" – to describe the apparent desire of PHEV drivers to avoid using gasoline *(6)*.

In this paper, we will investigate the idea of gas anxiety empirically, testing whether PHEV owners appear to place a premium on avoiding gasoline consumption. Using data from a web-based stated preference survey of real world PHEV drivers, we explore the following questions:

(1) What are the factors influencing a PHEV owner's decision of whether to charge or not at a public charging station?

(2) How the decision of is plug in or not affected by changes in gasoline price and charging price at public charge stations?

(3) Is there evidence that PHEV drivers value gasoline consumption differently than electricity consumption when making charging decisions?

BACKGROUND

PHEV ownership is growing steadily in U.S. According to the report of State of the Plug-in Electric Vehicle Market by Electrification Coalition, from its market debut (in 2011) to the middle of 2013, more than 110,000 plug-in electric vehicles had been sold, among which more than 66,000 were PHEVs. From the year 2013 to 2014, sales of PHEV continued to increase by 7% even though gasoline prices fell by more than 40% in 2014*(7)*. However progress on reducing gasoline dependency cannot be measured by sales figures alone. The magnitude of environmental benefits of these PHEVs depends on the percentage of VMT powered by electricity and the generation sources that supply that electricity *(8)*.

To assess the energy consumption and charging demand of PHEVs, early studies relied heavily on assumptions about the charging behavior of PHEV owners. For example, Kang and Recker assumed that PHEVs were only charged at home *(9)*.Lin and Greene assumed that PHEVs were plugged in whenever the CD range was depleted *(10)*. Axsen and Kurani assumed that PHEVs would be recharged whenever parked within 25 feet of an electrical outlet *(11)*. What these models of charging behavior have in common is that they are generally simple and deterministic. However in real world charging behavior is considerably more complicated than an empty battery or an available plug because multiple factors are involved in the decision making process and also charging choices are heterogeneous across users, which has been proved by some recent research *(8,12,13)*. Thus, it is critical to understand how PHEV owners' charging decisions are affected by the cost, speed, and availability of charging opportunities. Such knowledge enables the design of infrastructure systems so as to minimize the number of gasoline-fueled miles driven in PHEVs.

Initial research on charging behavior of PHEV drivers is basically descriptive and based on limited samples with many assumptions. Based on the daily travel distances of 255 households in Seattle over a one year period, Khan and Kockelman*(14)* found that for one-vehicle households, using PHEV with 40 miles of all electric range (PHEV40), 80% of their VMT will be electrified; for two-vehicle households, using a PHEV40, 50 to 70% of household miles can be electrified while meeting all trip-distance needs. Based on daily driving distances of 12 households in California, Williams et al. found "20 miles of charge-depleting range would have been fully utilized on 81% of days driven, whereas 40 miles would not have been fully utilized on over half of travel days." However, the authors note the limitations of the results due to the paucity of real world information *(15)*. Davies and Kurani reported results from a study of 40 vehicles for a one-week period during which the author identified a mean of one daily charge, including two participants that did not recharge at all *(16)*.

Based on a nationwide long-term PHEV travel data in the United States Zoepf et al. developed a mixed logit model of charging choices and found that current state of charge (SOC), trip distance and hours until next trip all influenced the choice of charging or not. Further what-if scenario analysis showed that for small-battery PHEVs (3 kWh), ubiquitous charging could save as much petroleum as quadrupling battery size *(8)*. The results also present heterogeneity of charging behavior across PHEV users, which has also been demonstrated through interviews *(8)* and other instrumented vehicle studies *(16)*.

In a word, in previous efforts of modeling of PHEV drivers' charging behavior, only the state of charge, characteristics of the trip (trip distance, hours until next trip), timing of charging and availability of charger have been included as independent variables. But some essential factors have not been studied yet, such as charging price, charging power, gasoline price. In this paper, based on a stated preference survey, we aim to find out how is the decision of plug in or not affected by changes in gasoline price and charging price at public charge stations.

METHODOLOGY

Survey Design

To elicit the effects of charging price, gasoline price, battery state of charge (SOC), and travel plans on charging decisions, we conducted a stated preference experiment in which the respondents were asked whether or not they would choose to recharge in each scenario.

Although stated preference data are often considered less reliable than revealed preference data, stated preference is a better and more practical choice for this particular research effort. First of all, the respondents in this survey were asked about a straightforward yes-or-no decision that they make on a regular basis in the real world. Since they were not being asked to choose among products or services that are not available or with which they have no experience, we believe the risk of hypothetical bias to be small.

There are significant obstacles to a revealed preference study on this subject. To do the analysis based on revealed preferences, we would need to know the real-time availability of Electric Vehicle Supply Equipment (EVSE), power and cost at each station, and the gasoline price, as well as having detailed data from instrumented vehicles. Other recent work (Yu and MacKenzie, under review) has shown that when working with revealed preference data, the particular methods and data sources used to infer charging station locations can materially affect the parameters of the resulting charging choice model. Moreover, it is challenging to capture the effect of gasoline prices on charging choices, since gasoline prices usually do not vary over a wide range in a short period of time. With the stated preference survey approach, these indicators were varied in different scenarios so we can identify their effects on people's choices.

The survey included two parts: (1)questionnaire on sociodemographic information and vehicle ownership (2) charging choice experiment.

(1) Background information.

The sociodemographic information was asked in the questionnaire, including: age, gender, education, household income, household size and zip code of home address. The following questions were asked about the car ownership of the household:

- ✓ How many vehicles in the listed category does your household own (or lease)?
  - ➢ Gasoline vehicles
  - ➢ Ethanol flex-fuel (E85) vehicles
  - ➢ Hybrid –electric vehicles (HEVs)
  - ➢ Plug-in hybrid-electric vehicles (PHEVs)
  - ➢ Battery –electric vehicles (BEVs)
  - ➢ other
- ✓ In what year did you purchase (or lease) your EV?
- ✓ Please briefly describe your motivation for purchasing an EV
- ✓ What is the primary function you drive your EV for? (Commuting to work, Daily household errands or other)
- ✓ What model of EV do you drive most frequently?

The following questions were asked about the EV use and charging patterns of the respondents:

- ✓ What range do you typically achieve from a full charge of your EV?
- ✓ Do you have a charger at home? (yes/no)
- ✓ Do you have a charger at work? (yes/no)
- ✓ Are there any other locations besides home or work at which you charge on a daily basis? (yes/no)
- ✓ How much do you pay for electricity at home? (Not sure, \$0.06-\$0.08 per KWh,

$0.09-$0.11 per KWh, and $0.12 + per KWh)

- ✓ What is the main generation source of your home electricity?
  - ➢ Coal
  - ➢ Hydroelectricity
  - ➢ Natural Gas
  - ➢ Nuclear
  - ➢ Oil
  - ➢ Renewables (wind, solar, geothermal, etc.)
  - ➢ Not sure
  - ➢ Prefer not to answer

(2) Charging choice experiments.

In this section, each respondent was presented with 8 scenarios. Under each scenario, they were asked to choose whether they thought they would charge at this station or not. A fractional factorial experimental design was used to generate the charging choice scenarios and unrealistic scenarios were deleted. The attributes and levels of the experiments are listed in TABLE 1.

TABLE 1 Attributes and Their Levels of the Experiments

Attributes	**Description**	**Attribute levels**
Charging price($/h)	The recharging price at the station	$0.5/h; $1.0/h; $1.5/h; $2.0/h; $5.0/h
Charging power(kW)	The charging speed at the station	1.9kw; 6.6kw
Dwell time(h)	The time duration for which the respondent will stay at this station	0.25h; 0.50h; 1h; 2h; 4h; 8h
Distance to home(mi)	Distance from this station to home	2mi; 5mi; 10mi; 20mi; 30mi; 50mi
Remaining range (mi)	The current remaining range of the PHEV	Distance to home - 20mi; Distance to home - 10mi; Distance to home - 5mi; Distance to home - 2mi; Distance to home + 2mi; Distance to home + 5mi; Distance to home + 10mi; Distance to home + 20mi;
Gasoline price ($)	Gasoline price	$2.5/gallon; $3/gallon; $3.5/gallon; $4/gallon; $4.5/gallon

We recruited the respondents through the Electric Auto Association (EAA). Electric Auto Association members are generally enthusiastic about electric vehicle technology and related research, and were willing to participate into the survey without any extrinsic incentives. Since all of them own at least one electric vehicle, they are familiar with types of choices they were being asked about, so their preferences when it comes to recharging can be captured precisely. Respondents were distributed around the United States (FIGURE 1).

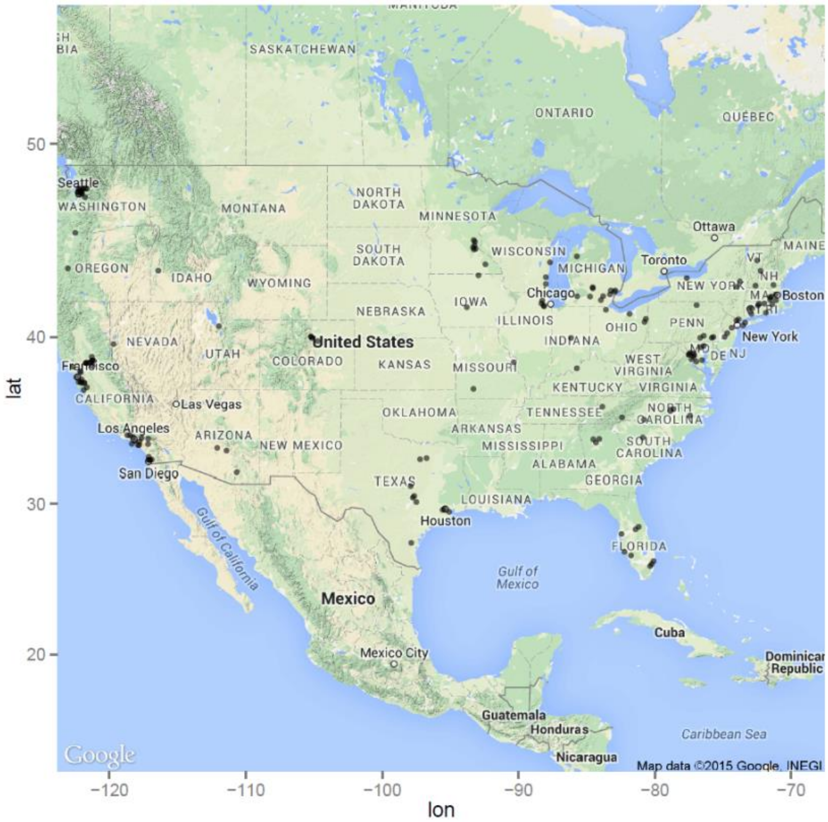

FIGURE 1 Distribution of the respondents.

Data Description

The data was collected from November 12th 2013 to February 12th 2014. 177 PHEV owners participated into this survey but only 157 of the responses were valid. The respondents distributed around the country as shown in Figure 1. A large proportion of the respondents were from west coast and east coast. The geographical distribution of the respondents means that the actual range of PHEVs probably varies quite significantly even for the same PHEV make/model, because of the variability in climate across the county *(17).*

A descriptive analysis of the sample is shown in Table 2. The respondents were generally older (65% are more than 45 years old) and 85% of the respondents were male. The household income among the respondents is generally higher than average (mostly between \$80,000 to \$140,000). Among the 177 respondents, 28% do not own a conventional gasoline car in the household.

TABLE 2 Description of the Sample

Variable	Category	Frequency	Percentage
Age	18-34	19	11%
	35-45	42	24%
	46-55	53	30%
	55+	62	35%
	Prefer Not to Answer	1	1%
Gender	Male	151	85%
	Female	22	12%
	Prefer Not to Answer		0%
Education	Less than High School	1	1%
	High School / GED	3	2%
	Some College	25	14%
	2-Year College Degree (Associates)	16	9%
	4-Year College Degree (BA, BS)	79	45%
	Master’s Degree	34	19%
	Doctoral Degree	7	4%
	Professional Degree (MD, JD)	10	6%
	Prefer Not to Answer	2	1%
Household income	<$19,999	0	0%
	$20,000-$39,999	2	1%
	$40,000-$59,999	5	3%
	$60,000-$79,999	13	7%
	$80,000-$99,999	29	16%
	$100,000-$119,999	29	16%
	$120,000-$139,999	59	33%
	$140,000+	20	11%
	Prefer Not to Answer	20	11%
household size	1	22	12%
	2	74	42%
	3	30	17%
	4	35	20%
	5	14	8%
	6	2	1%
Number of gasoline vehicles in household	0	50	28%
	1	74	42%
	2	28	16%
	3	15	8%
	4	12	7%

Modeling Method

In prior efforts to capture the heterogeneity of charging behavior across BEV and PHEV drivers, mixed logit regression model were mainly used *(8,12,13)*. In a continuous mixed logit regression model, the random taste of coefficients follows a random distribution across the population. The probability of charging of respondents i under the situation t is by taking the integral over the distribution of taste coefficients β:

$$P(Charge_{it}|\beta) = \int \frac{e^{\beta^T X_{it}}}{1 + e^{\beta^T X_{it}}} f(\beta|\cap) d\beta \qquad (1)$$

Here the utility function is: $U_{it} = V_{it} + \varepsilon_{it} = \beta^T X_{it} + b^T Z_{it} + \varepsilon_{it}$. β is the fixed effects and b represents the random effects that captures the heterogeneity of charging behavior. The preference across all the respondents is considered heterogeneous. The assumption of the distribution of the random tastes needs to be made before the estimation of the model *(18).*

Latent class model assumed that all individuals can be separated into finite assumed sets of classes (Q classes). The taste heterogeneity is captured by allocating respondents to different classes with different taste coefficient in a probabilistic manner that is in conjoint with respondents' socio-demographic information. Within each class, the random taste is considered homogeneous *(19).*

Within class q, the conditional probability of charging by individual i in choice situation t is:

$$\mathrm{P}(Charge_{it}|\, \beta_q, \text{class q}) = \frac{\exp(X_{it}\beta_q)}{\exp(X_{it}\beta_q) + 1} \qquad (2)$$

β_q, coefficient vector of class q
X_{it}, observed variables for charging model

The probability of respondent i falling into class q is defined as π_q, it can be calculated as the following equation:

$$\pi_q = \frac{e^{X_i' \gamma_q}}{\sum_{q=1}^{Q} e^{X_i' \gamma_q}} \qquad (3)$$

γ_q, coefficient vector of class allocation model
X_i', observed variable for class allocation model

Then the charging probability for individual i at the situation t is:

$$P(Charge_{it}|\beta) = \sum_{q=1}^{0} \pi_q \cdot \frac{\exp(X_{it}\beta_q)}{\exp(X_{it}\beta_q) + 1} \qquad (4)$$

In this paper we use a latent class logit model to capture the factors influencing the charging choices and the heterogeneity across the PHEV users. A comparison of mixed logit models and latent class models by Hess et al. shows that both mixed logit model and latent class model produce significant gains in performance compared to the conventional logit model, since these models capture heterogeneity in consumer choices among observations. However, latent class logit models generate richer patterns of heterogeneity by linking the class allocation to demographic and socio-economic indicators, and they are much easier to interpret than mixed logit models *(19)*.

MODELING CHARGING CHOICE USING THE LATENT CLASS LOGIT MODEL

Derivation of Variables

In order to address our research questions, we derive variables that represent amount of energy obtained (how much energy can be attained at this station) and costs (including the gasoline costs and electricity costs) based on the characteristics of the scenarios (charging price, charging power, gas price, remaining range and distance to destination) and the characteristics of the PHEVs driven. In this section, we explain how these variables were calculated.

Energy Obtained

Energy obtained can be measured by the three derived variables: range obtained (mi), electricity obtained (kWh), and percentage of range obtained (%).

(1) Range obtained

Range obtained is the maximum range increase the PHEV can get at the station during the dwell time if the owner chooses to charge. If the dwell time is enough for the PHEV to get a full range, then the range obtained will be $full\ range(mi) - remaining\ range(mi)$. Otherwise it needs to be calculated according to the charging speed (charging power) and dwell time. It is calculated as following:

$$range\ obtained(mi) = Min\{\frac{charging\ power(kWh) \times dwell\ time\ (h)}{electricity\ consumption\ rate(kWh/mi)}\ , full\ range(mi) - remaining\ range(mi)\}$$

(2) Electricity obtained

$$electricity\ obtained(kWh) \times = range\ obtained\ (mi) \times electricity\ consumption\ rate\ (kWh/mi)$$

(3) Percentage of range obtained

$$percentage\ of\ range\ obtained = \frac{range\ obtained\ (mi)}{full\ range(mi)}$$

In order to test which of these three variables of energy obtained is the best predictor of PHEV drivers' charging decisions, three preliminary models were estimated. According to the Bayesian Information Criterion (BIC) values, the variable percentage of range obtained generates the best goodness of fit. One possible explanation is that the respondents consider the relative amount of range they can get at each station to make the decision. For example, the ability to add 10 miles of electric range is almost a full charge for a Toyota Prius Plug-In, but only ¼ of a charge for a Chevrolet Volt. Under this explanation, Prius owners will be more likely to charge at this station than Volt owners. Therefore percentage of range obtained will be used in the following analysis.

One important note is that in all the calculations shown here, the full range is the reported range obtained from the survey. Reported range has proved to be a better predictor of charging decision according to the model fit, which could be because of the following two reasons: 1) because the survey was conducted during winter and the respondents distributed across the country, the full range of PHEVs varies greatly in different climates since in cold areas there are great range loss *(17)*; 2) the reported range incorporates different driving patterns across respondents.

Costs

When an PHEV driver makes the recharging decision, three costs could be involved into the consideration: how much needs to be paid at the station for recharging (charging cost at this stop); how much needs to be paid to get back to the full range after the trip (electricity cost at home); and how much needs to be paid for gasoline if the PHEV runs out of electricity during the trip (gasoline cost). In this section, how these variables are calculated will be demonstrated in detail.

(1) Charging cost at this stop

One variable that will be useful is the cost at this stop, which means the total charging cost if an individual chooses to charge at this station. We calculate this as:

$$\text{Cost at this stop}(\$) = \text{Price}\ (\$/h) * \text{Plug time}\ (h)$$

Plug time is the time duration that the PHEV stays plugged on the charger. If the car cannot get full range during the dwell time, plug time will be equal to the dwell time. So we calculate plug time as:

$$\text{Plug time}\ (h) = \min\left(\text{dwell time}\ (h),\ \frac{(\text{full range}(mi) - \text{remaining range}(mi)) \times \text{electricity consumption rate}(kWh/mi)}{\text{charger power}(kW)}\right)$$

(2) Electricity cost at home

Electricity cost at home is the amount of money needs to be paid to get the PHEV back to full range after the trip. It depends on PHEV driver's decision of whether charge at this station or not. If the respondent chooses to charge, the range after charging can be calculated as:

$$\text{range after charging}\ (mi) = \text{remaining range}\ (mi) + \text{range charged at this station}\ (mi)$$

If range after charging is smaller than distance to home, when the driver arrives home, the range of the PHEV will be zero. Otherwise if range after charging is enough for the driver to get home using electricity, when he/she arrives home, the range of the PHEV will be: $\text{range after charging}(mi) - \text{distance to home}(mi)$.

So the electricity cost at home can be calculated as:

$$\text{electricyt cost at home}_{charge}(\$) = \begin{cases} \text{full range}(mi) \times ECR\ (kWh/mi) \times EPH(\$/kWh), & \text{if range after charging}(mi) \le \text{distance to home}(mi) \\ \{\text{full range}(mi) - (\text{range after charging}(mi) - \text{distance to home}(mi))\} \times ECR\ (kWh/mi) * EPH(\$/kWh), & \text{if range after charging}(mi) > \text{distance to home}(mi) \end{cases}$$

EC: electricity consumption rate (kWh/mi)

EPH: electricity price at home ($/kWh)

When the respondent chooses not to charge at this station, if the remaining distance is smaller than distance to home, when he/she arrives home the range of the PHEV will be zero. Otherwise if remaining distance is bigger than distance to home, when he/she arrives home the range of the PHEV will be: $remaining\ range(mi) - distance\ to\ home(mi)$. So the electricity cost at home will be:

$$electricyt\ cost\ at\ home_{not\ charge}(\$) = \begin{cases} full\ range(mi) \times ECR\ (kWh/mi) \times EPH(\$/kWh), & if\ remaining\ range(mi) \leq distance\ to\ home(mi) \\ \{full\ range(mi) - (range\ after\ charging(mi) - distance\ to\ home(mi))\} \times ECR\ (kWh/mi) * EPH(\$/kWh), & if\ remaining\ range(mi) > distance\ to\ home(mi) \end{cases}$$

EC: electricity consumption rate (kWh/mi)
EPH: electricity price at home ($/kWh)

(3) Gasoline cost

If the respondent chooses to charge at this station, the gasoline cost is:

$$gas\ cost_{\ charge}(\$) = \begin{cases} 0, & if\ range\ after\ charging(mi) \geq distance\ to\ home(mi) \\ \frac{distance\ to\ home(mi) - range\ after\ charging(mi)}{fuel\ economy(mi/gallon)} \times gas\ price\ (\$/gallon), & if\ range\ after\ charging(mi) < distance\ to\ home(mi) \end{cases}$$

If the respondent chooses to charge at this station, the gasoline cost is:

$$gas\ cost_{\ not\ charge}(\$) = \begin{cases} 0, & if\ remaining\ range(mi) \geq distance\ to\ home(mi) \\ \frac{distance\ to\ home(mi) - remaining\ range(mi)}{fuel\ economy(mi/gallon)} \times gas\ price\ (\$/gallon), & if\ remaining\ range\ (mi) < distance\ to\ home(mi) \end{cases}$$

Variables for the Class Allocation Model

The following social demographic variables were selected for the class allocation model: gender, income, and education. In addition, we include the following variables about the respondent's ownership and usage of the PHEV: How many years have the respondents been using electric vehicles (years of EV ownership), whether the source of electricity at home is renewable (electricity source renewable or not) and whether there are gasoline cars in the household (no gasoline car) were also included as class allocation factors. Based on an open ended question in the questionnaire on the motivation of the respondents choosing to use electric vehicles, the following two variables are coded:

(1) Environmental concern: only mentioned environmental concern as a motivation for using EVs;

(2) Financial benefits: only mentioned financial benefits as a motivation for using

EVs.

A descriptive analysis of variables involved in this analysis is provided in TABLE 3.

TABLE 3 Descriptive Analyses of Variables Involved

variable name	details	number	percentage
Male	1, male	138	88%
	0, female	19	12%
High income	1, income higher than $140,000	57	36%
	0, other	100	64%
Education	1, Less than Bachelor Degree	43	27%
	2, Bachelor Degree	73	46%
	3, Master Degree	28	18%
	4, Doctor Degree	5	3%
	5, Professional Degree	8	5%
Years of owning/ leasing EV	Continues variable. max: 10 years; min: 1 year; mean: 1.6		
Electricity source at home is renewable or not	1, renewable electricity source at home?	35	22%
	0, non-renewable electricity source	122	78%
No gasoline car owned/ rented in the household	1, no conventional gasoline vehicle was owned/rented in the household	45	29%
	0, other	112	71%
Environment concern as the only motivation of owning/leasing EV	1, only indicated environment concern as the motivation	60	38%
	0, other	97	62%
Financial benefits as the only motivation of owning/leasing EV	1, only indicated financial benefits as the motivation	34	22%
	0, other	123	78%
Percentage of range could be obtained (%)	Continues variable. Max: 0.933; min: 0; mean: 0.29.		
Charging cost at this stop ($)	Continues variable. Max: 16; Min: 0; Mean: 1.965		
Electricity cost at home if chose to charge ($)	Continues variable. Max: 9.93; Min:0.05; Mean: 1.58		
Electricity cost at home if chose not to charge ($)	Continues variable. Max: 9.93; Min:0.18; Mean: 2.05		
Gas cost if chose to charge ($)	Continues variable. Max: 1.824; Min: 0; Mean: 0.1156.		
Gas cost if chose not to charge ($)	Continues variable. Max: 2.189; Min: 0; Mean: 0.2923.		

Latent Class Model

A latent class logit model was estimated to identify the factors influencing the choice of whether to charge. Percentage of range obtained, charging cost at this stop, electricity cost at home, and gasoline cost are included as independent variables in the model. The model specifications are the same for all classes.

Utility for charge at this station is:

$$U_{charge} = \beta_0 + \beta_1 \cdot percentage\ of\ \text{range obtained} + \beta_2 \cdot charging\ cost\ at\ this\ stop + \beta_3 \cdot electricity\ cost\ at\ home_{charge} + \beta_4 \cdot gasoline\ cost_{charge} + \varepsilon_{charge}$$

Utility for not charge at this station is:

$$U_{not\ charge} = \beta_3 \cdot electricity\ cost\ at\ home_{not\ charge} + \beta_4 \cdot gasoline\ cost_{not\ charge} + \varepsilon_{not\ charge}$$

Model specification for the class allocation model:

Utility of class allocation model for class 1:

$$U_{class\ 1} = \gamma_0 + \gamma_1 \cdot Male + \gamma_2 \cdot HighIncome + \gamma_3 \cdot BachelorDegree + \gamma_4 \cdot MasterDegree + \gamma_5 \cdot DoctorDegree + \gamma_6 \cdot PrefessionalDegree + \gamma_7 Years\ of\ EV\ ownership + \gamma_8 \cdot No\ gasoline\ car + \gamma_9 \cdot Renewable\ electrity\ + \gamma_{10} \cdot Environment\ concern + \gamma_{11} \cdot Financial\ benefits + \ \varepsilon_1$$

Utility of class allocation model for class 2:

$$U_{class\ 2} = 0$$

The latent class model with two classes was applied and the results were shown in Table 4. The BIC of this model is 1259.8, much smaller than the BIC of binary logit model: 1506.9. Models with larger numbers of classes were also tested, but they did not converge. Different specifications of the class allocation models were also tested and the one with the smallest BIC value is chosen as the final model.

TABLE 4 Results of Latent Class Model

	Class 1				Class 2			
	Est.	Std. err	t-test	p-value	Est.	Std. err	t-test	p-value
Intercept (β_0)	-0.76	0.18	-4.19	<0.01	-0.18	0.15	-1.18	0.24
percentage of range obtained (β_1)	3.24	0.77	4.20	<0.01	3.76	0.80	4.68	<0.01
charging cost at this stop (β_2)	-2.69	0.36	-7.55	<0.01	-0.52	0.07	-7.25	<0.01
electricity cost at home (β_3)	-0.85	0.31	-2.72	0.01	-0.69	0.33	-2.08	0.04
gasoline cost (β_4)	-2.89	0.60	-4.84	<0.01	-1.95	0.49	-3.98	<0.01
Class allocation model	**Class 1**				**Class 2**			
	Est.	**Std. err**	**t-test**	**p-value**	**Est.**	**Std. err**	**t-test**	**p-value**
Intercept (γ_0)	1.31	0.84	1.56	0.12	-	-	-	-
Male (γ_1)	0.29	0.61	0.47	0.64	-	-	-	-
High income (γ_2)	-0.34	0.45	-0.74	0.46	-	-	-	-
Education- Bachelor Degree (γ_3) (Reference level: less than bachelor degree)	-0.32	0.52	-0.62	0.54	-	-	-	-
Education- Master Degree (γ_4) (Reference level: less than bachelor degree)	-1.17	0.65	-1.80	0.07	-	-	-	-
Education- Doctor Degree (γ_5) (Reference level: less than bachelor degree)	0.56	1.26	0.45	0.65	-	-	-	-
Education- Professional Degree (γ_6) (Reference level: less than bachelor degree)	0.13	0.97	0.13	0.9	-	-	-	-
Years of owning/leasing EV (γ_7)	-0.76	0.31	-2.44	0.01	-	-	-	-
No gasoline car (γ_8)	-0.56	0.45	-1.24	0.22	-	-	-	-
Electricity source renewable or not (γ_9)	0.753	0.55	1.37	0.17	-	-	-	-
Environment concern as the only motivation of owning/leasing EV (γ_{10})	0.18	0.46	0.39	0.70	-	-	-	-
Financial benefits as the only motivation of owning/leasing EV (γ_{11})	1.28	0.59	2.16	0.03	-	-	-	-
Membership probability	31%				69%			

Shading indicates statistical significance (p-value less than 0.05)

The model results are shown in table 4. With the classification variables of class 2 being normalized to 0, two class factors are significant: Years of EV ownership and financial benefits as the only motivation of owning/leasing EV. According to the coefficients of these two variables, respondents who are relatively new adopters of EVs and who mainly considered financial benefits as the only motivation are more likely to be allocated into class 1. They tend to make their charging decision based on the monetary spending and energy obtained at this station. The charge cost at the station and gas cost both have negative influence on the utility of charging and the magnitudes are quite similar according to the coefficients (-2.69 and -2.89), which indicates that this group of people value expenditures on gasoline and on public charging stations quite similarly. For them there is no evidence of gas anxiety. The fact that the absolute value of the coefficients of the electricity cost at home is much lower (-0.849) indicates that this group people are more willing to spend more money to charge at home.

The PHEV users who bought/leased EV for a longer period of time (earlier adopters) and did not consider financial as the only motivation are more likely to be assigned to class 2. They also make charging decision based on monetary costs and the range attained. However, comparing the coefficients, the magnitudes of gas cost and charge cost are quite different: gas cost has a much larger magnitude (-1.95) than charge cost (-0.519). This indicates that this group of people weight expenditures on gasoline more heavily than expenditures on charging. This can be interpreted as one form of “gas anxiety.”

After calculating the expected value of the probability of every respondent being in each class, we got the membership probability of 31% for class 1 (no evidence of gas anxiety) and 69% for class 2 (with gas anxiety) across respondents in this sample. With the increase of years of ownership, PHEV users are more likely to be grouped into class 2 – to value gasoline cost more than charging cost. This could be because of the increase of familiarity with the charging system or change of their sustainability awareness. Either way, with the growth of the number of EV adopters and the improvement of charging infrastructure, there will be more people willing to pay more for electricity instead of gasoline.

CONCLUSION

Based on a survey among a group of PHEV owners, this work evaluated how charging price and gasoline price influence people’s stated choices of whether or not to charge at a public station. The results of a latent class model show that there two basic types of PHEV users with respect to recharging decisions at public charging stations. One type includes early adopters and those who did not consider financial benefits as their only motivation of owning a PHEV. This group values gas expenditures much more heavily than electricity expenditures. This could be interpreted as a form of “gas anxiety”: people are willing to spend more on charging at a public station even though using gasoline for the rest of the trip would save them money. The other group tends to be newer adopters and people who identified financial savings as their only motivation for owning an EV. This group tends to value gasoline cost and charging cost at the station quite similarly, and values electricity expenditures at home less than other costs. There is no evidence of gas anxiety among this group of people; they appear willing to consume gasoline if doing so is cheaper than charging.

This model of decision making highlights the heterogeneity of charging preferences among PHEV owners. The evidence of gas anxiety among some PHEV owners means some drivers will recharge more frequently than has been assumed in the past. This group of owners can be expected to make greater use of public charging infrastructure, and is willing to pay a relatively high amount for public charging. However, another group of users is more likely to charge when doing so will reduce their travel costs, but is less likely to pay a premium to avoid consuming gasoline.

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