Environmental and Resource Economics (2019) 74:131–157
https://doi.org/10.1007/s10640-018-00312-9

Demand for Green Refueling Infrastructure

Tamara L. Sheldon[1] · J. R. DeShazo[2] · Richard T. Carson[3]

Accepted: 19 December 2018 / Published online: 2 January 2019

Abstract

Despite increasing public investment in charging infrastructure for plug-in electric vehicles (PEVs), policymakers know little about drivers' preferences for publicly-accessible charging stations. Using data from an innovative choice experiment, we estimate demand for PEV charging stations, characterizing willingness to pay for access to types of locations as well as driver tradeoffs between refueling duration and costs. Prospective PEV drivers are willing to pay the actual variable cost of recharging at public charging stations and are willing to pay to cover significant fixed costs at select locations. Not surprisingly, many prospective drivers reveal a positive willingness to accept to wait while refueling, but this varies greatly across latent classes.

Keywords Choice experiment · Transportation policy · Clean transportation · Electric vehicles

✉ Tamara L. Sheldon
Tamara.Sheldon@moore.sc.edu

J. R. DeShazo
deshazo@ucla.edu

Richard T. Carson
rcarson@ucsd.edu

[1] Department of Economics, University of South Carolina, 1014 Greene St., Columbia, SC 29208, USA

[2] Luskin School of Public Affairs, University of California, 337 Charles E Young Dr E, Los Angeles, CA 90095, USA

[3] Department of Economics, University of California, 9500 Gilman Dr., La Jolla, San Diego, CA 92093, USA

1 Introduction

Policymakers have adopted an array of public policies designed to increase the installation of electric vehicle charging stations in support of their long-term goal of increasing the adoption of plug-in electric vehicles (PEVs).[1] The presumption behind these policies is that drivers will be more likely to purchase PEVs if they are certain they can refuel them at convenient locations within their daily travel patterns. One recent study estimates that a policy subsidizing charging infrastructure could have been twice as effective as the federal tax credit at promoting PEV adoption (Li et al. 2017). Policymakers also seek to reduce vehicle emissions by maximizing the number of electric vehicle miles traveled. Accordingly, federal and state policymakers have offered very large subsidies, in the form of grants, rebates, tax exemptions, and sales tax exemptions, to incentivize the installation of charging stations.

The central question for policymakers is determining where charging infrastructure should be sited in order to maximize social welfare. Without a well functioning market, policymakers confront several practical decisions when designing these subsidy policies. They must choose between siting charging stations that support (i) local travel (work and routine daily trips) versus (ii) regional travel along interstates or freeways (e.g. corridor charging). They must select among a range of possible land use destinations (workplaces, malls, grocery stores, gyms, etc) that may host these charging stations. Furthermore, they must decide what type of charger technologies to site at these locations. Level 2 chargers[2] are slower but less expensive while fast chargers are more expensive. When making these decisions, policymakers would benefit from knowing drivers' willingness to pay for refueling with electricity, which involves estimating their marginal rate of substitution between time costs and fuel costs savings for electric refueling.

In this paper, we use information on consumers' preferences to help inform each of these practical policy questions while stopping short of undertaking a complete welfare analysis. First, how range-anxious are drivers? We characterize the distribution of prospective drivers' preferences towards refueling for their current gasoline vehicle and the prospective PEV. This is relevant to policy because the larger the share of risk-averse drivers, and the more risk-averse they are, the greater the number of charging stations will be needed to induce PEV purchases.

Second, we ask what the perceived benefits of infrastructure are at alternative locations to drivers. More precisely, we measure drivers' willingness to pay for the costs of charging infrastructure at specific locations. We assess Level 2 charging infrastructure at locations that include workplaces, grocery stores, malls, schools, as well as fast charging infrastructure along freeways and near drivers' homes. We also explore whether heterogeneity across drivers significantly changes their valuation of these charging stations. The relatively significant fixed costs associated with charging station construction (Williams and DeShazo

[1] PEVs include both battery electric vehicles (BEVs) and plug-in hybrid vehicles (PHEVs). BEVs are powered exclusively by electricity from the on-board battery, while PHEVs are powered by both electricity and gasoline, having both a battery and gasoline engine on board.

[2] There are three types of charging infrastructure that support plug-in electric vehicles, each of which offers progressively faster charging times. Level 1 charging involves 110V charging from standard building electrical outlets. Level 2 offers 220V and 240V charging from dedicated chargers. Fast charging offers much higher voltage and is often comparable to gasoline refueling in terms of wait times.

2014) make the selection of locations with relatively higher driver willingness to pay essential to ensuring the financial viability of stations.

Third, we assess whether, and how much, drivers will actually pay for additional miles of electric travel when refueling. We ask drivers to assume they are driving a plug-in hybrid electric vehicle (PHEV), since this affords them the greatest flexibility in refueling options. We then give drivers a choice set of refueling alternatives that include traditional gas stations as well as battery refueling options, each varying in their refueling time and refueling cost per mile. In our analysis, we also explore how differing driver characteristics influence their use of, and willingness to pay for, additional electric range. With this information, policymakers are in better position to predict whether and how much different types of charging station will be used by PEV drivers of different types.

This study contributes to the literature by being one of the first economic studies to investigate driver demand for green refueling infrastructure. Numerous transportation engineering studies have used a variety of optimization algorithms to site charging stations based on access costs, battery state of charge, charging levels, existing traffic patterns, grid impacts, and other technical factors (Sweda and Klabjan 2011; Eisel et al. 2014; Jia et al. 2014). However, none of these analyses are based explicitly on drivers' (i) preferences for refueling, (ii) location-specific preferences or (iii) marginal rate of substitution between costs and refueling wait times.

Using stated preference data from a representative survey of 1261 California new car buyers, we estimate discrete choice models that allow us to address the aforementioned questions. Our analysis utilizes a Bayesian D-efficient experimental design that enables more efficient estimation of the parameters of interest.

We estimate two models that allow us to explore heterogeneity of preferences for charging from different angles. First, we estimate a mixed logit model that allows for the estimated preference parameters to randomly vary. Second, we estimate a latent class model, which provides insight into what consumer characteristics tend to be associated with different aspects of the preference parameter distributions and allows us to uncover customer profiles of market segmentation.

2 Background

California is a useful case study because of its early prioritization of charging infrastructure development and associated plug-in electric vehicle adoption. California, both as part of regional efforts and on its own, has large investments in charging infrastructure, totaling over $400 million from 2010 to 2016. First, in 2007, the U.S. Department of Transportation designated six interstate routes as "Corridors of the Future" with the goal to reduce traffic congestion.[3] The Interstate 5 that connects California, Oregon, and Washington was one of the corridors, and $15 million was provided to these states to improve highway conditions, as well as installing charging infrastructure for the Electric Highway Initiative.[4] Second, in California, a "$120 million settlement between the California Public Utilities Commission

[3] "U.S. Department of Transportation Names Six Interstate Routes as 'Corridors of the Future' to Help Fight Traffic Congestion." Federal Highway Administration, U.S. Department of Transportation. September 10, 2007. http://www.fhwa.dot.gov/pressroom/dot0795.cfm.

[4] "Corridor: Interstate 5 (I-5)- Washington to California." Corridors of the Future Fact Sheet. Federal Highway Administration, U.S. Department of Transportation. http://www.fhwa.dot.gov/pressroom/fsi5.cfm.

and NRG Energy Inc. will fund the building of a network of charging stations for battery electric vehicles."[5] Third, the California Public Utilities Commission also approved an agreement totaling over $227 million dollars that allows the state's largest investor owned electrical utilities to rate base the costs of installing 12,500 chargers.[6] Fourth and finally, the California Energy Commission has allocated over $60 million from the electric public investment charge to support regional and local government investment and planning from 2010 through 2015 through the Alternative and Renewable Fuel and Vehicle Technology Program.[7]

While the transportation engineering literature has provided guidance on siting these stations, the economics literature, with its focus on benefits and costs, is underdeveloped. Many transportation approaches to location are based on optimization routines that take into consideration access costs, battery state of charge, charging levels, existing traffic patterns, grid impacts, and other technical factors (Eisel et al. 2014; Jia et al. 2014). Sweda and Klabjan (2011) developed an agent-based decision support system that incorporates residential ownership patterns with daily driving patterns to identify optimal locations. Perhaps the best engineering siting approach is that of Chen et al. (2013), whose algorithm minimizes EV users' station access costs while penalizing unmet demand as measured by each vehicle's state of charge.

However, the preferences of electric vehicle drivers for siting may diverge from these engineering estimates for several reasons. First, drivers may exhibit preferences for refueling PEVs that differ from those revealed when they refuel internal combustion engines. Observers have hypothesized that BEV drivers will be averse to running out of electricity as compared to drivers of conventional vehicles. Second, PHEV drivers may exhibit a strong environmental preference to travel on electric miles, thereby representing different refueling preferences. Third, the early adopters of PEVs, for which we are making siting decisions now, may differ from those of the general population that underlie historical driving patterns.

Various stated preference studies on alternative fuel vehicles include refueling time or availability as attributes (e.g., Bunch et al. 1993; Brownstone et al. 2000; Ewing and Sarigöllü 2000; Potoglou and Kanaroglou 2007; Hidrue et al. 2011; Qian and Soopramanien 2011; Achtnicht et al. 2012). However, for EV alternatives, refueling time usually refers to at-home charging time, and refueling availability is not location specific (e.g., 50% of service stations). Two recent papers explore public charging preferences in more depth. Ito et al. (2013) include fuel availability as an attribute in a stated preference vehicle choice experiment, with EV alternatives being rechargeable only at home or at both home and supermarkets. Although they use their estimates to predict alternative fuel vehicle market shares in Japan under various scenarios, their estimates could also be used to calculate a willingness to pay (WTP) for the option to recharge EVs at supermarkets. Scasny et al. (2015) incorporate recharging time and fast charging availability in a stated preference

[5] See http://www.greentechmedia.com/articles/read/NRG-Settlement-Funds-Californias-Electric-Expressway-EV-Charger-Network.

[6] The CPUC approved SCE to install 1500 at the cost of up to $22 million, SDG&E to install 3,500 at the costs of up to $45 million and PG&E to install 7,500 at a cost of up to $160 million. See https://www.csis.org/analysis/utility-involvement-electric-vehicle-charging-infrastructure-california-vanguard.

[7] See Fig. 5 in the "California statewide plug-in electric vehicle infrastructure" by NREL, 2014. This program was authorized by Assembly Bill 118 (Nùñez, Chapter 750, Statutes of 2007) instructing California Energy Commission to develop and deploy alternative and renewable fuels and advanced transportation technologies to help attain the state's climate change policies.

vehicle choice experiment. They calculate WTP for medium and high availability of fast charging stations in Poland of €1340 and €2060, respectively.

We further explore location-specific public charging preferences using choice experiments focusing on alternative refueling scenarios independent of vehicle choice. Embedding charging attributes in a vehicle choice decision answers an important question—how much are drivers willing to pay up front for a vehicle, given existing charging infrastructure? We attempt to answer a fundamentally different question—once a driver owns a plug-in hybrid, what are her location specific charging preferences and how does she trade off public refueling cost and wait times? The first question, answered by the existing literature, informs policy makers as to how public charging investments can encourage EV adoption. The second question, answered in this paper, can inform policy makers as to where to situate and how much to charge for public charging infrastructure.

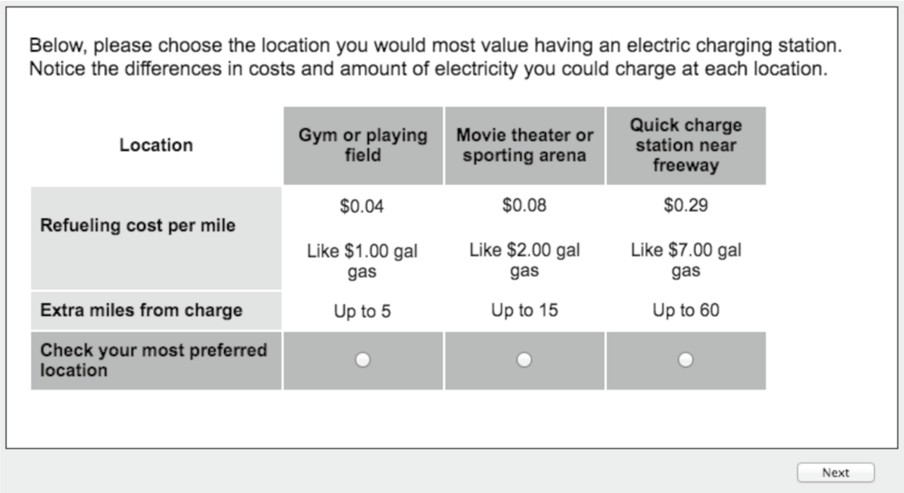
3 Data

3.1 Survey Design

We administered an online survey to a representative sample of prospective Californian new car buyers in December of 2013 and obtained a sample of 1261 completed surveys. The survey was conducted by the internet provider The GfK Group using samples from KnowledgePanel® and an opt-in sample provider SSI, with each accounting for approximately half of the final sample. KnowledgePanel® members may have been recruited by either the former random digit dialing (RDD) sampling or the current address-based sampling (ABS) methodologies. The KnowledgePanel® recruitment begins as an equal probability sample. To account for any non-coverage or non-response, a set of study-specific post-stratification weights was constructed. The post-stratification adjustment was applied based on demographic distributions from the November 2013 Current Population Survey. Post-stratification variables include gender, age, race, education, census region, household income, household ownership status, metropolitan area, and internet access.

A short screener survey was sent to potential respondents. This screener included nine simple demographic questions, asked whether or not the respondent purchased or leased a new car in the past, and asked whether or not the respondent planned to purchase or lease a new car in the next five years. Of the 2,429 KnowledgePanel® members sampled, 1515 (62.4%) completed the screener. Of the 38,300 SSI individuals sampled, 1464 (3.5%) completed the screener. Of those who completed the screener, 638 and 624 of each sample, respectively, qualified for the main survey by being 18 or more years of age and indicating that he or she plans to purchase or lease a new vehicle in the next three years. All respondents who qualified proceeded to complete the survey, for a total of 1261 responses. The introduction to the survey emphasized its consequentiality by informing respondents that the study was being done by the University of California to "help the State of California better plan for the future transportation needs of households like yours." The main survey then gathered household, vehicle, and demographic data. We presented respondents with questions related to the importance of refueling convenience as an attribute of their new vehicle. We also assessed respondents' attitudes for alternative refueling practices for both gasoline and electric vehicles.

Respondents were provided with information on BEV and PHEV technologies and introduced to PEV attributes, including refuel price and electric range, as well as charging


Below, please choose the location you would most value having an electric charging station. Notice the differences in costs and amount of electricity you could charge at each location.

Location	Gym or playing field	Movie theater or sporting arena	Quick charge station near freeway
Refueling cost per mile	$0.04 Like $1.00 gal gas	$0.08 Like $2.00 gal gas	$0.29 Like $7.00 gal gas
Extra miles from charge	Up to 5	Up to 15	Up to 60
Check your most preferred location	○	○	○

Next

Fig. 1 Example choice set from charging location module

requirements. After a choice experiment eliciting demand for PEV attributes (which we refer to as the vehicle choice module)[8] a second choice experiment presented different potential charging options, including charging stations at various public locations, as well as quick charge stations.[9] The respondent, for instance, was told that quick charge stations "are just like gas stations. You would wait 15 minutes to fully charge your vehicle. However, quick charging stations will be more expensive than other charging stations." The respondent was then asked to pick the location she would prefer to charge at, given the cost of charging and how many miles of charge could be obtained. We refer to this module as the "Charging Location Module." Each respondent was shown three choice sets. An example choice set from this module is shown in Fig. 1. Attribute levels are displayed in Table 1.

In the next module, which we refer to as the "Charging Scenario Module," respondents were asked to imagine they are in the following situation:

"In this section, we are going to ask you some questions about how you would choose to refuel in different situations. Imagine that you are in the driver's seat of a dual-fuel vehicle. So it has a gas tank and a battery...Driving home from work, you realize that your gas tank is empty, but you have to make an important stop that is ten miles out of the way. You have enough battery charge to make it to the stop, but not enough battery charge to make it home afterwards. You pass by an electric charging station as well as a gas station on your way. If the following were your options, which of these options would you choose for refueling?"

The respondent then chose amongst three different recharging options and also had the "status quo" option to refuel at a gasoline station. Each respondent was shown three choice sets. An example choice set from this module is shown in Fig. 2 and attribute levels are displayed in Table 1.

[8] For more details on this module, see Sheldon et al. (2017).

[9] The charging choice experiments were only administered to respondents who chose some sort of PEV (approximately 85% of the respondents) at least once in the previous choice experiment. Respondents who never chose a PEV were not administered the charging choice experiments, as they were unlikely to view these choices as relevant or realistic.

Imagine you are in the situation:

Driving home from work, you realize that your gas tank is empty, but you have to make an important stop that is ten miles out of the way. You have enough battery charge to make it to the stop, but not enough battery charge to make it home afterwards. You pass by an electric charging station as well as a gas station on your way. If the following were your options, which of these options would you choose for refueling?

	Option 1	Option 2	Option 3	Option 4
Scenario	Refuel at the gasoline station.	Recharge your battery.	Recharge your battery.	Recharge your battery.
Refueling time	15 minutes	30 minutes	15 minutes	120 minutes
Refueling cost per mile	$0.21 Like $5.00 gal gas	$0.13 Like $3.00 gal gas	$0.25 Like $6.00 gal gas	$0.04 Like $1.00 gal gas
Total cost of trip extension (= 10 miles x per mile cost)	$2.08	$1.25	$2.50	$0.42
Check your most preferred location	○	○	○	○

Next

Fig. 2 Example choice set from charging scenario module

Similar to Golob Thomas et al. (1997) and Bunch et al. (1993), refueling costs are shown as cost per mile. However, feedback from our focus groups suggests that consumers prefer thinking of refueling costs in terms of the cost of a gallon of gasoline. Therefore, similar to Hidrue et al. (2011), we also show refueling costs as "Like $X gal gas." To help respondents better understand, upon introduction of the refueling cost attribute before the vehicle choice experiment, we explain (customizing the bracketed information) "Recall that you said your preferred [Toyota RAV4 SUV] got about [24] mpg so it costs about [$0.17] per mile to drive at $4.00/gal for gas. The cost of electricity varies around California but the typical all-electric vehicle might cost you about $0.08 per mile. If you preferred vehicle were all-electric, it would be like being able to buy gas at [$1.92]/gal as shown below."

To fully charge, a discharged battery may take up to 10 hours using a Level 2 charger, as most PEV owners have installed at home. Realistically, a consumer plugging in to a public charging station for an hour or two might not get more than 5 or 10 miles worth of charge, while a consumer plugging in for the better part of the day may get 30 or 40 miles worth. For example, the range attribute descriptions that we offer (up to 5 miles or up to 10 miles) is consistent with actual Level 2 charging rates given the typical time in residence for each type of location—e.g., a gym/playing field (1.5 hours in residence) or a movie theater/sporting arena (2.5 hours in residence). The survey explains to respondents that charging is slow, most PEV drivers charge overnight, and the only way to get a full charge in a short amount of time is with quick charging stations, which tend to be more expensive. Note that in Table 1, slow, medium, and fast charge are not separate

Table 1 Attribute levels

Charging location module		
Location	Extra miles	Refuel cost[a] ($/gal equivalent)
Work	15, 20, 30, 40	$1, $2, $3, $4, $5, $6, $7
Transit	15, 20, 30, 40	$1, $2, $3, $4, $5, $6, $7
Gym	5, 10, 15, 20	$1, $2, $3, $4, $5, $6, $7
Mall	5, 10, 15, 20, 30	$1, $2, $3, $4, $5, $6, $7
Quick near home	60, 80	$4, $5, $6, $7
Quick near freeway	60, 80	$4, $5, $6, $7
Grocery	5, 10, 15	$1, $2, $3, $4, $5, $6, $7
School	5, 10, 15, 20	$1, $2, $3, $4, $5, $6, $7
Entertainment	10, 15, 20	$1, $2, $3, $4, $5, $6, $7
Charging scenario module		
Refuel option	Refuel time (minutes)	Refuel cost[a] ($/gal equivalent)
Gasoline/status quo	10, 15	$4, $4.5, $5
Slow charge	60, 120	$1, $1.5, $2, $2.5
Medium charge	30, 60	$2, $2.5, $3, $4
Fast charge	15, 30	$3, $4, $5, $6, $7

[a] At the time the survey was administered, average gasoline cost in California was approximately $4 per gallon, the average overnight electricity rate in California was roughly 16 cents per kWh, and the average vehicle economy of electric vehicles was 3.5 miles per kWh. This equates to an average cost per electric mile of $0.046. The average cost per mile of gasoline vehicles in the vehicle universe used in the survey is $\frac{\$4/\text{gal}}{20\text{mi/gal}}$ = $0.20 per mile. Thus on average, refueling cost for electric miles is 23% of the $4 per gallon refueling cost for gasoline miles, or $0.92/gal. Therefore we choose a baseline electric refueling cost of $1.00 per gallon equivalent, roughly equal to the price of provision. Prices go up from there, either to recover costs of infrastructure or because of higher electricity prices

attributes. However, each choice set includes a refuel time and cost from each of these three rows such that each respondent sees a slow but cheaper option, a fast but more expensive option, and a third recharging option in between.

We used NGENE software to design the choice experiments. We sought experimental designs to minimize the variance of the estimated coefficients of the specified utility functions assumed to underlie the multinomial logit models to be estimated. The efficiency of an experimental design can be greatly improved if we know the approximate magnitude or even just the sign of the true parameters (Scarpa and Rose 2008). For example, by assuming that the coefficient on price is negative, or that consumer utility for an alternative is reduced as that alternative gets more expensive, we no longer need an experimental design that can distinguish between a negative or positive coefficient, but can instead more precisely estimate the magnitude of a negative price coefficient.

Specifically, we use an algorithm in NGENE that allows us to maximize the amount of information we are able to extract from our choice experiment by minimizing the variance-covariance estimator of the vector of utility function coefficients. The algorithm searches through potential experimental designs with different combinations and levels of attributes. We select the experimental design with the smallest determinant of the asymptotic variance-covariance matrix, also known as the D-error.[10] To further increase the efficiency of the design, we specify Bayesian priors for the refueling cost, refueling time, and extra mile attributes. That is, for these coefficients, we specify an assumed *a priori* distribution. We base these assumptions on parameter estimates from pretest results and for refuel time, we also base the assumption on results from a study by Ewing and Sarigöllü (2000).

Table 9 in the "Appendix" gives definitions of all the variables used in our analysis, all of which were collected in the survey.

3.2 Comparison of Survey Sample and Population Data

In order to validate the new car buyer survey data, we cross-check the respondent characteristics with a sample of new car buyers from the Caltrans 2010-2012 California Household Travel Survey (Caltrans 2013), the nearest such study in time to December 2013 when this paper's survey was administered. These comparisons, shown in "Appendix" Table 8, reveal that for 12 diagnostic variables our survey sample is very similar to the actual new car buying population. Income, education and age are included in Table 8, exhibiting modest differences for a few value categories.[11]

4 Empirical Models

The standard multinomial logit can model the probability of selecting a charging option over other alternatives. In this model, a respondent selects the charging option that gives her greater utility than any other available alternative. The utility of each alternative is a function of its attributes. The estimated coefficients tell us how a change in each attribute (e.g., refuel time) impacts utility.

Individual n receives utility U_{ni} from choosing alternative i:

$$U_{ni} = V_{ni} + \varepsilon_{ni}. \tag{1}$$

The probability of individual n selecting alternative i is the probability her utility from i is greater than her utility from choosing any other available alternative:

$$\pi_{ni} = Prob\left(V_{ni} + \varepsilon_{ni} \geq V_{nj} + \varepsilon_{nj}\right); \quad \forall j \neq i. \tag{2}$$

If we assume ε_{ni}'s are independently distributed Type-I extreme value errors and a linear utility function, such that $V_{ni} = \mathbf{x_i'}\boldsymbol{\beta}$, where $\mathbf{x_i}$ is a vector of attributes of i and $\boldsymbol{\beta}$ is a vector of parameters, then we can model the probability of individual n choosing alternative i as:

$$\pi_{ni} = \frac{exp\left(\mu_n \mathbf{x_i'}\boldsymbol{\beta}\right)}{\sum_{j=1}^{J} exp\left(\mu_n \mathbf{x_j'}\boldsymbol{\beta}\right)}, \tag{3}$$

[10] For more details see Scarpa and Rose (2008).

[11] The weighted California Household Travel Survey, relative to our weighted sample, exhibits modestly fewer upper middle households ($75–100k; 15% compared to 23%) and greater upper income households (>$150K; 21% compared to 12%). With respect to age, it exhibits a lower number of 18–24 year olds (2% compared to 16%), modestly greater 55–64 years olds (28% compared to 14%) and greater 65+ year olds (19% compared to 10%). With respect to education, it contains fewer households with less than a high school diploma (3% compared to 7%), fewer with a high school degree (11% compared to 25%) and greater with graduated degrees (26% compared to 13%). Finally, with respect to home ownership, it has modestly greater households that own their homes (77% compared to 62%).

where μ_n is a scale parameter commonly assumed to equal 1.

In this model, the coefficients are fixed, effectively assuming that all respondents have the same preferences. The logit model exhibits the independence of irrelevant alternatives (IIA), meaning that the odds of choosing vehicle j over vehicle k are independent of the choice set for all pairs j, k, which may imply unrealistic substitution patterns. The standard logit model does not allow for heterogeneity of preferences.

The first model we estimate that relaxes this assumption is a mixed logit. In the mixed logit model, developed by Train (1998), the coefficients of the utility function are random parameters for which we can specify a distribution. For example, if we assume a coefficient is normally distributed, we estimate both the mean and standard deviation of that coefficient. This model allows for heterogeneous preferences across respondents and does not necessarily exhibit the IIA property, thereby allowing for more flexible substitution patterns.[12] Structurally, the mixed logit model is similar to the standard logit except the parameters of the utility function are assumed to be random, not fixed, and the probability of individual n selecting alternative i becomes:

$$\pi_{ni} = \int \frac{exp\left(\mu_n \mathbf{x_i'}\boldsymbol{\beta}\right)}{\sum_{j=1}^{J} exp\left(\mu_n \mathbf{x_j'}\boldsymbol{\beta}\right)} f(\boldsymbol{\beta}|\boldsymbol{\theta})\partial\boldsymbol{\beta}, \tag{4}$$

where $f(\boldsymbol{\beta}|\boldsymbol{\theta})$ is the density function of $\boldsymbol{\beta}$.

A drawback of the mixed logit model is that it does not tell us where different respondents are in the estimated distribution of preferences.[13] In other words, it does not tell us which type of respondents have which preferences.

In between the multinomial and mixed logit models is the latent class model, which segments the population into different classes, where preferences for each class are estimated separately, and class membership of respondents is determined by their characteristics.

Assume existence of S segments in a population. The probability of consumer n choosing alternative i conditional on membership in segment s, where $s = 1, \ldots, S$, is:

$$\pi_{ni|s} = \frac{exp\left(\mathbf{x_i'}\boldsymbol{\beta}_s\right)}{\sum_{j=1}^{J} exp\left(\mathbf{x_j'}\boldsymbol{\beta}_s\right)}. \tag{5}$$

Allowing latent membership for segmentation to be:

$$M_{ns}^{*} = \mathbf{y_n'}\boldsymbol{\lambda}_s + \zeta_{ns}, \tag{6}$$

[12] For example, the multinomial logit estimated in Table 2 assumes that if an alternative such as grocery store charging were not available, the probability that had been assigned to choosing the grocery store would be equally split amongst the remaining alternatives. In contrast, the mixed logit estimated in Table 2 would allocate the probability according to the parameter distributions and the covariance between preferences for remaining alternatives and for grocery store charging.

[13] While it is possible to make the mean or variance of a mixed logit parameter a function of observed covariates, we ran into frequently incurred problem that such models with more than one or two covariates tend to be numerically unstable and would not converge to a well-defined maximum value. Individual taste parameters can be identified as detailed in Revelt and Train (1999), although the authors caution that estimating a mixed logit as a function of observed covariates such as demographics is 'more direct and more accessible to hypothesis testing than estimating a mixed logit without these characteristics, calculating expected tastes, and then doing cluster and other analyses on the expected tastes.'

where

M^*_{ns}: membership likelihood function for individual n to be in segment s
$\mathbf{y_n}$: vector of both psychometric constructs and socioeconomic characteristics
$\boldsymbol{\lambda}_s$: vectors of parameters
ζ_{ns}: independently distributed Type-I extreme value errors

we can model the probability of consumer n belonging to segment s as:

$$\pi_{ns} = \frac{exp\left(\mathbf{y}'_{\mathbf{n}}\boldsymbol{\lambda}_s\right)}{\sum_{s=1}^{S} exp\left(\mathbf{y}'_{\mathbf{n}}\boldsymbol{\lambda}_s\right)}. \tag{7}$$

The probability of consumer n choosing alternative i is the the sum across segments of the probability of her selecting alternative i conditional on segment membership times her probability of segment membership:

$$\pi_{ni} = \sum_{s=1}^{S} \pi_{ns}\pi_{ni|s} \tag{8}$$

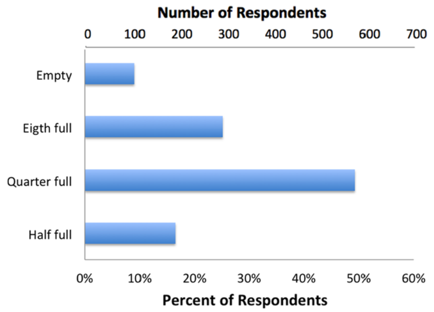
$$\pi_{ni} = \sum_{s=1}^{S} \frac{exp\left(\mathbf{y}'_{\mathbf{n}}\boldsymbol{\lambda}_s\right)}{\sum_{s=1}^{S} exp\left(\mathbf{y}'_{\mathbf{n}}\boldsymbol{\lambda}_s\right)} \frac{exp\left(\mu_s\mathbf{x}'_{\mathbf{i}}\boldsymbol{\beta}_s\right)}{\sum_{j=1}^{J} exp\left(\mu_s\mathbf{x}'_{\mathbf{j}}\boldsymbol{\beta}_s\right)}. \tag{9}$$

5 Results

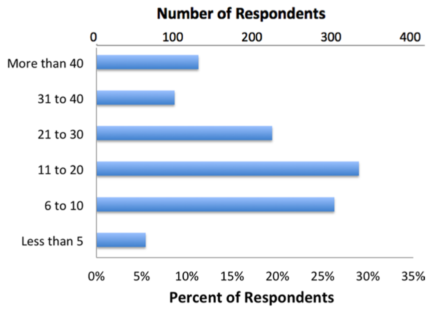
5.1 Refueling Perceptions and Attitudes

Earlier studies have suggested consumers may be reluctant to purchase PEVs because of "range anxiety" (Kurani et al. 1996; Kitamura and Hagiwara 2010; Franke et al. 2012). When asked to choose which factor is the most important in choosing a new vehicle, the most respondents chose reliability, ahead of fuel economy, price, and safety. Having enough electric range and a dependable charging infrastructure are likely to influence consumer perceptions of reliability of a vehicle. "Charging inconvenience" (44%) was the second most popular reason, after "too expensive" (56%), cited by the 186 respondents who did not choose a PEV in the vehicle choice module as to why they did not choose a PEV. Limited range is not a default option for this question. The respondents answering this question did not choose any BEV or PHEV. While insufficient range is a rational reason for not choosing a BEV, the same is not true for PHEVs, which have similar ranges to ICEs. Nevertheless, respondents could fill in an "other" reason. Of the 28 respondents who selected "other," only one individual's stated reason was related to range.

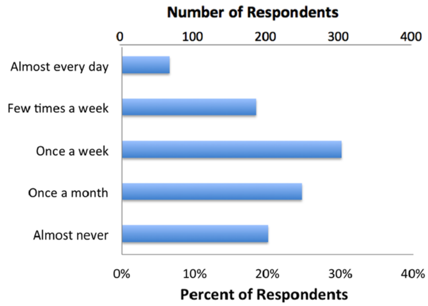
To determine the efficient deployment of charging stations for a population, policymakers benefit from understanding how drivers' attitudes towards refueling are distributed across the population. Individual refueling decisions involve a tradeoff between costs and an undesirable outcome, namely running out of fuel. Drivers face the time costs of



(a) What is the reading on the fuel gauge when you typically decide to refuel at a gas station?



(b) How many miles of electric range would you feel comfortable returning home with?



(c) If you were to purchase a PHEV with 30 miles of electric range, about how often do you think you would you use gasoline mode?

Fig. 3 Refueling and recharging perceptions

searching for, and traveling to, refueling infrastructure as well as any time costs associated with refueling. Drivers minimize their aggregate refueling costs over time by driving until they are nearly out of fuel, thereby minimizing their aggregate number of refueling events. However, because drivers do not have perfect foreknowledge of driving conditions and trip distances, they face a tradeoff between minimizing refueling costs and minimizing the risk of running out of fuel.

Figure 3 shows respondent attitudes towards refueling/recharging. Figure 3a shows that the majority of respondents prefer to refuel their current vehicles when the gasoline tank is a quarter full, if not fuller. This suggests that even with conventional vehicles, drivers are averse to running out of fuel, with only a small minority typically waiting for the empty light to come on to refuel. Figure 3b shows the electric range respondents would be comfortable returning home with. The most respondents chose 11 to 20 miles of range, although many chose more and very few chose fewer than 5 miles. These results are similar to Fig. 3a, suggesting that refueling attitudes are similar amongst potential PEV drivers.

Despite the desire to return home with an electric range buffer, the majority of respondents anticipates using gasoline mode once a week to once a month if they drove a PHEV, as shown in Fig. 3c. Approximately a fifth of respondents believe they would almost never need to use gasoline mode, while less than 10% would need gasoline

Table 2 Charging locations

	Multinomial logit			Mixed logit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Mean	SD	Mean	SD
Extra miles	0.016***	0.017***	0.016***	0.027***	0.017*	0.028***	0.019***
	(0.003)	(0.003)	(0.003)	(0.005)	(0.009)	(0.005)	(0.006)
Refuel cost	− 0.318***	− 0.321***	− 0.318***				
	(0.033)	(0.033)	(0.033)				
ln(-refuel cost)				− 0.899***	1.875***	− 0.749***	− 1.812***
				(0.232)	(0.276)	(0.185)	(0.415)
Work	0.716***		0.716***	0.862***	− 1.121***		
	(0.155)		(0.155)	(0.211)	(0.403)		
Work*employed		1.012***				1.193***	0.612
		(0.164)				(0.212)	(0.633)
Grocery	0.915***	0.901***	0.915***	1.138***	0.814**	1.071***	0.562
	(0.159)	(0.152)	(0.159)	(0.193)	(0.323)	(0.187)	(0.465)
Mall	0.549***	0.529***	0.549***	0.484**	1.274***	0.433**	1.224***
	(0.156)	(0.144)	(0.156)	(0.218)	(0.415)	(0.205)	(0.452)
Quick near home	0.512**	0.443**	0.512**	0.505*	0.389	0.403	− 0.384
	(0.214)	(0.205)	(0.214)	(0.285)	(0.960)	(0.250)	(0.417)
Quick by freeway	0.471**	0.406**	0.471**	0.590**	− 1.322***	0.511**	− 1.165***
	(0.196)	(0.185)	(0.196)	(0.284)	(0.385)	(0.251)	(0.402)
Transit	0.040	0.002	0.040	− 0.218	1.425***	− 0.328	− 1.476***
	(0.158)	(0.149)	(0.158)	(0.252)	(0.488)	(0.235)	(0.437)
Gym	− 0.292*	− 0.306*	− 0.292*	− 1.020***	1.909***	− 1.238***	2.091***
	(0.171)	(0.163)	(0.171)	(0.377)	(0.547)	(0.384)	(0.477)
School	− 0.365 **	− 0.395**		− 0.714***	1.142***	− 0.827***	1.156***
	(0.173)	(0.165)		(0.275)	(0.408)	(0.303)	(0.378)
School*student			− 0.365**				
			(0.173)				
Observations	9,540	9,540	9,540	9,540	9,540	9,540	9,540
AIC	5,960	5,923	5,960	5,806	5,806	5,763	5,763
BIC	6,031	5,995	6,031	5,950	5,950	5,907	5,907

Weighted to represent population of CA new car buyers Robust standard errors in parentheses, clustered by respondent ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Location coefficients estimated relative to omitted category “charging at entertainment venue”

mode almost everyday. Although a major benefit of PHEVs is the flexibility to use either gasoline or electric mode, a large majority of potential PHEV drivers believe they would primarily use electric mode. As PHEV batteries tend to be smaller than BEV batteries, using PHEVs mainly in electric mode is likely to require reliable access to non-home-based charging.

Table 3 Charging locations: willingness to pay

	Multinomial logit†			Mixed logit††		
	Median	LB†††	UB†††	Median	LB	UB
Per extra mile	$0.05	$0.03	$0.07	$0.04	$0.02	$0.08
Work*employed	$3.15	$2.08	$4.40	$1.59	$0.84	$3.45
Grocery	$2.81	$1.85	$3.91	$1.43	$0.75	$2.96
Mall	$1.65	$0.77	$2.59	$0.58	$0.03	$1.52
Quick near home	$1.38	$0.18	$2.69	$0.54	-$0.08	$1.48
Quick Near freeway	$1.26	$0.24	$2.46	$0.68	$0.07	$1.67
Transit	$0.01	– $0.91	$0.95	– $0.44	– $1.42	$0.18
Gym	– $0.95	– $2.02	$0.03	– $1.65	– $3.52	– $0.63
School	– $1.23	– $2.32	– $0.20	– $1.10	– $2.54	– $0.32

†Estimates are generated from Column 2 of Table 2

††Estimates are generated from Columns 6 and 7 of Table 2

†††LB is the lower bound and UB is the upper bound of the 95% confidence intervals

5.2 Charging Locations

Public charging station provision depends on consumers willingness to pay for both the variable costs of charging and the amortized costs of the charge station. Willingness to pay for charging at different locations may depend on relative convenience of charging at various locations, how long a driver spends at different locations, and how frequently a driver visits different locations. In order to estimate willingness to pay across charging locations, we capture consumer tradeoffs between convenience and cost in the Charging Location Module. In these choice experiments, as shown in Fig. 1, respondents are asked to assume they own a PHEV and to choose the charging location where they would most value having a charging station. The refueling costs and extra miles from the charge vary across locations as shown in Table 1.

Table 2 shows the results of the multinomial logit and mixed logit model estimation using the choice experiment data from the Charging Location Module. Assuming they decide to recharge in a public location, respondents get the most utility from charging at grocery stores and work, followed by the mall and at quick chargers near both home and the freeway. The omitted category is charging at an entertainment venue, which provides more utility than charging at the gym or at school, which provide the least utility. Charging stations at a particular location will only be useful for drivers who visit those locations. For example, a charging station located at a place of work will only be useful for drivers who commute to work, and will not be useful for students, unemployed persons, or retirees. Therefore in Columns 2, 6, and 7 we interact work location with an indicator for employment. Similarly, in Column 3 we interact school location with an indicator for student. We do not have demographic information that would be a reliable indicator for those who travels to the other locations. Columns 2, 6, and 7 show that workplace charging is the most valuable charging location for respondents who work. Surprisingly, charging at school does not provide more utility for students, as shown in Column 3. Column 2 is our preferred multinomial logit specification, as the employment interaction results in a lower AIC and BIC than alternative specifications. Similarly, Columns 6 and 7 are our preferred mixed logit specifications. We assume that the refuel cost coefficient is lognormally distributed, which results in a better model fit (lower AIC and BIC) than assuming a normal distribution.

Table 3 displays willingness to pay, conditional on choosing to charge away from home.[14,15] Respondents are willing to pay around \$0.02–\$0.08 per mile of charge. The location specific values can be thought of as per charging occasion access fee premiums relative to the omitted category (entertainment venue). Relative to the omitted category, respondents are willing to pay up to a \$3 premium to charge at the grocery store, near work, and at quick charge stations. Respondents would expect a discount of \$1 to charge at the gym/sports facilities or at school. At the time the survey was administered, average gasoline cost in California was approximately \$4 per gallon, the average overnight electricity rate in California was roughly 16 cents per kWh, and the average vehicle economy of electric vehicles was 3.5 miles per kWh. This equates to an average cost per electric mile of \$0.046. We find that consumers are willing to pay around \$0.04–\$0.05 per extra mile.

As shown in Table 3, respondents expressed premium and discounted values for location-specific charging. Using the multinomial logit estimation results, respondent were willing to pay \$3.15 more for workplace Level 2 charging (when they were employees), \$2.81 for Level 2 grocery store access, \$1.65 for Level 2 mall access, \$1.38 for quick charging access near their homes, and \$1.26 for quick charging access along freeways. The mixed logit median WTP estimates are somewhat smaller: \$1.59 for workplace, \$1.43 for grocery stores, \$0.58 for malls, \$0.54 for quick charging near home, and \$0.68 for quick charging access along freeways. This suggest that respondents are willing to pay over and above the variable costs for access to charging at these locations, which might allow charging station operators to recover all or a portion of their fixed costs. As shown in Table 3, relative to the omitted category respondents did not positively report valuing access to Level 2 charging, on average, at gyms or schools.

Importantly, preferences and willingness to pay for various charging locations above are conditioned on cost per extra mile of charge. Within our survey, we found that not controlling for the cost of charging leads respondents to overstate their preferences for freeway fast charging relative to other charging locations. For example, in the survey we asked respondents to rank several factors in terms of which factors would make them more likely to purchase a PEV. We modeled the rank ordering of these factors with respect to the probability of purchasing a PEV. The results are shown in Table 4. The coefficients represent ordered log-odds coefficients and represent how important the factors are relative to the omitted factor, which is "charging stations at mall or grocery store." Respondents indicate

[14] Multinomial choice questions involving private goods are not necessarily incentive compatible even when the survey itself is consequential. This is because a respondent must balance an increase in the likelihood that the good is made available for purchase against an increase in the price charged if offered. As such, estimates can potentially be biased in either direction. Because our estimates are lower than fuel cost per mile for almost all gasoline vehicles and in the same general range as home charging costs, if a bias exist it is likely to be in a downward direction.

[15] Our focus is on demand by the early and mid-market PEV adopters who are in our sample. Respondents who never chose electric vehicles were not administered the charging modules. Marginal willingness to pay for public charging is likely higher for respondents with a higher probability of owning a PEV. Since respondents who never chose electric vehicles were not administered the charging modules, the aggregate demand for charging at non-home stations in the longer-term future is likely underestimated here, to the extent households represented by these respondents later buy electric vehicles as their attributes including price and range improve and gasoline prices increase as California's actions to reduce carbon dioxide and other air pollutants become increasingly stringent.

Table 4 Charging factors that contribute most to selecting a PEV (rank-ordered logit)

Quick charging near freeways	0.481***
	(0.050)
Workplace charging	0.355***
	(0.050)
Quick charging near commute	− 0.110**
	(0.051)
HOV access	0.373***
	(0.050)
Observations	1261
AIC	12,670
BIC	12,697

Weighted to represent population of CA new car buyers Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Coefficients estimated relative to omitted category "charging stations at mall or grocery store"

that quick charging stations near freeways would make them most likely to purchase a PEV, followed by free single-occupant high-occupancy vehicle (HOV) lanes access[16] and workplace charging. However, when ranking their preferences, respondents are not told to assume charging time or price would vary across locations. In the Charging Location module, however, respondents must make tradeoffs between the convenience of different locations and the charge time and price. Table 2 suggests that once price is taken into account, consumers prefer charging at the grocery store, at work, or near the mall to the relatively expensive quick charging stations. An important policy takeaways is that while consumers might express great interest in quick charging stations, they may not be willing to pay the requisite premium. Once willingness to pay is taken into account, public charging stations at other locations might more effectively increase PEV adoption.

Results from Table 3 could be used to predict revenue implications for proposed public charging stations in various locations. Combined with an estimate of how frequently drivers are anticipated to use a charge station, our estimates could predict feasible revenue with reasonably tight confidence intervals. Alternatively, our estimates could be used to calculate the daily user base required to cover the amortized costs of a charge station.

5.3 Charging Scenarios

In Sect. 5.2 we analyze consumer preferences and willingness to pay across different public charging locations, given that the consumer has decided to recharge. In this section, we estimate willingness to pay to refuel with gasoline versus recharging a PHEV and characterize consumer tradeoffs between refuel cost and time. In the Charging Scenario Module, respondents are asked to imagine they are driving a PHEV and need to decide how to

[16] In California, PEV drivers are currently able to access HOV lanes free of charge. Research indicates this policy has had a significant positive impact on PEV sales in the state (Sheldon and DeShazo 2017). Our results indicate that development of public charging infrastructure could be equally if not more successful in promoting PEV adoption in California.

Table 5 Charging scenarios: mixed logit

Variables	Mean	SD
Status quo	− 0.052	− 2.274***
	(0.170)	(0.285)
Refuel time	− 0.040***	− 0.040***
	(0.006)	(0.006)
Refuel cost	− 0.386***	− 0.402***
	(0.054)	(0.078)
Observations	12,704	12,704
AIC	6642	6642
BIC	6709	6709
Covariances		
	Refuel time	Refuel cost
Status quo	0.030***	− 0.092
	(0.006)	(0.100)
Refuel time		− 0.376***
		(0.083)

Weighted to represent population of CA new car buyers Robust standard errors in parentheses, clustered by respondent $***p < 0.01$, $**p < 0.05$, $*p < 0.1$

The preferred specification for the mixed logit estimation assumes that the refuel cost parameter is normally distributed. This results in a lower log pseudolikelihood, lower AIC, and lower BIC than assuming the refuel cost parameter is log normally distributed

refuel for a ten mile trip extension.[17] Choices include the status quo option of refueling at a gas station and three recharging options that vary in refuel time and cost.[18] An example choice set is shown in Fig. 2 and attribute levels are shown in Table 1. Based on our pre-testing, we presented respondents with two different measures of the cost per distance traveled. The first measure is the cost per mile. The second measure, in order to render the first measure more mentally accessible, if framed and scaled up, represent the aggregate costs of a ten-mile trip. This second framing, rendered as a trip with a well-understood distance, also avoided a "small numbers" bias that some respondents experience when trying rely solely upon the per mile cost. Using data from these choice experiments, we first estimate a mixed logit module to characterize the distribution of preferences for refueling

[17] Because having to recharge one's vehicle battery is an unfamiliar act for the respondents, the survey includes over 8 screens describing how recharging works as well as what the private costs and benefits of doing so are. We pre-check respondent knowledge of, and ability to distinguish, PHEVs from BEVs. We do not present this choice scenario to the 38 respondents who fail this pre-check. In this choice experiment, we place the respondent in PHEVs not only because it enables us to better a critical policy issue (increasing share of PHEV miles driven using electricity) but also because PHEVs more closely resemble ICEs than would a BEV. Importantly, PHEVs are not range limited while offering the driver flexibility to decide whether to recharge or not. Our pretesting revealed that by this point in the survey, respondents could conceptualize the time-cost trade-off that choosing the recharge represented for them.

[18] At the time the survey was conducted, public charging stations were not common, which is why refueling at the gas station was likely to be perceived by respondents as a status quo.

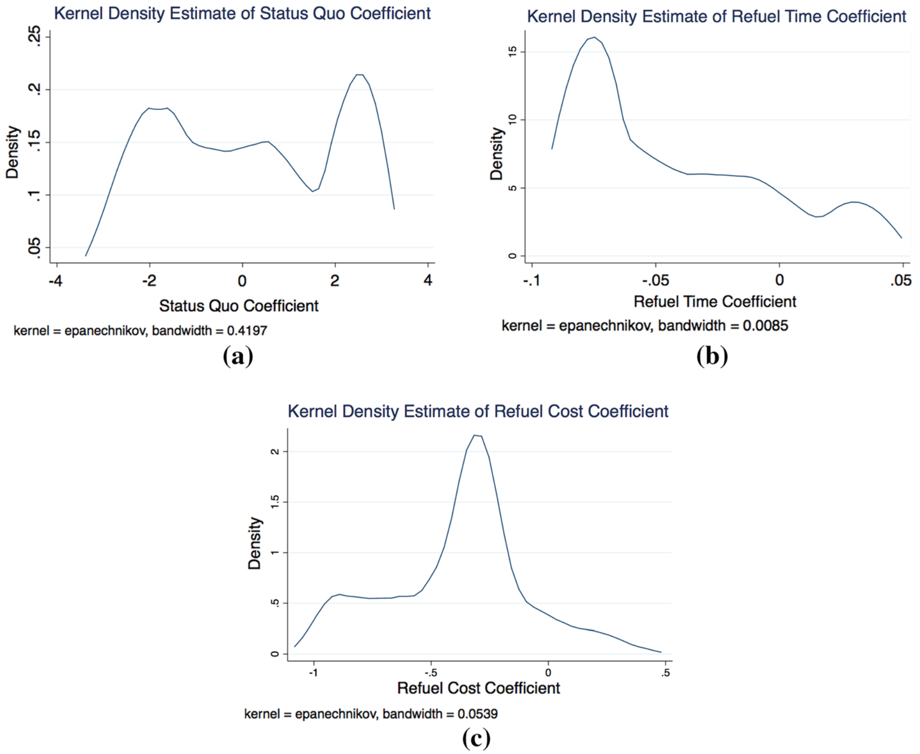


Fig. 4 Charging scenarios: mixed logit coefficient distributions

versus recharging, refuel time, and refuel cost. Then, we estimate a latent class model to further investigate the heterogeneity of these preferences.

Mixed Logit Model Table 5 shows the results of the mixed logit model estimation using the choice experiment data from the Charging Scenario Module. The mean coefficient for the status quo parameter, which indicates if the respondent chose to refuel the PHEV with gasoline rather than charge, is zero and not statistically significant. However, the standard deviation of the distribution of the coefficient is large and significant. The mean coefficients on refuel time and refuel cost are -0.04 and -0.39, respectively, and highly statistically significant. Consistent with economic intuition, these results suggest a distaste for waiting longer or paying more for refueling.

In the mixed logit estimation, we allow the random coefficients to be correlated. In addition to estimating the mean of the coefficients, we also estimate all the elements of the variance-covariance matrix. As shown in the bottom part of Table 5, the covariance between status quo and charge time is positive and highly significant, meaning that a respondent who has a relatively stronger preference against a longer charge time is more likely have a stronger preference against the status quo, and vice versa. The covariance between refuel time and refuel cost is negative and highly statistically significant. This suggests that more price sensitive consumers are less time sensitive and vice versa. This makes sense because lower income individuals tend to be more price sensitive and may also have a lower value of time.

Table 6 Goodness of fit by number of latent classes

Classes	LLF	No. param	AIC	CAIC	BIC
2	− 3483.84	7	6981.68	7023.51	7016.51
3	− 3355.00	11	6732.00	6797.74	6786.74
4	− 3307.80	15	6645.60	6735.25	6720.25
5	− 3292.87	19	6623.75	6737.30	6718.30
6	− 3278.91	23	6603.82	6741.28	6718.28
7	− 3273.79	27	6601.58	6762.94	6735.94
8	− 3266.54	31	6595.08	6780.34	6749.34

To further explore the parameter distributions, we use the method proposed by Revelt and Train (1999) to calculate individual-level parameters. We plot kernel density estimates of these individual-level parameters in Fig. 4a–c. Figure 4a shows that preferences for the status quo option are bimodal with peaks around positive 2.5 and negative 2. This means that while many respondents have a strong preference for the status quo, many others have a strong preference to recharge with electricity instead of refuel with gasoline.

Figure 4b shows that while some respondents are relatively indifferent to charge time, a majority of respondents strongly prefer shorter charge times. Figure 4c shows preferences for refueling cost to be roughly normally distributed. The average charge time coefficient translates to a mean willingness to pay of \$0.10 per minute decrease in charge time for a 10-mile charge. In other words, respondents would need to be compensated \$1.00 for each additional ten minutes of wait time while refueling for a 10-mile trip extension. Although the implied value of time (\$6 an hour) seems low, further analysis reveals a wide distribution around this estimate. Furthermore, drivers could engage in other activities such as working, shopping, or seeing a movie simultaneously as their vehicle charges, which could help to explain this low implied value of time. We next turn to the latent class model to further understand the heterogeneity driving these preference parameter distributions.

Latent Class Model The mixed logit model allows for heterogeneous preferences across respondents and allows for more flexible substitution patterns. Although we are able to use the mixed logit estimation to predict the distribution of charging preferences, the mixed logit model does not inform us as to the drivers of this heterogeneity—e.g., which populations have the strong preferences for and against the status quo charging option. To explore the drivers of charging preference heterogeneity, we estimate a latent class model.

To determine our model specification, we first estimate models assuming two to eight latent classes. More classes allow us to better identify heterogeneity but also require more power. Table 6 shows the Akaike information criterion (AIC), Bayes information criterion (BIC), and consistent AIC (CAIC)[19] for each of the seven models. The model with 8 classes has the lowest AIC, the model with 4 classes has the lowest CAIC, and the model with 6 classes has the lowest BIC. Prior research has found that the AIC tends to overestimate the number of latent classes in finite mixture models (Nylund et al. 2007). Therefore we proceed in our analysis assuming 5 latent classes, which is a compromise between the CAIC and the BIC.

[19] The CAIC, introduced by Bozdogan (1987), is an extension to the traditional AIC that make it “asymptotically consistent and penalize overparameterization more stringently to pick only the simplest of the ‘true’ models.”

To identify which types of consumers belong to which segment (i.e., class), we include a set of membership characteristics and estimate how each of these characteristics impacts probability of belonging to each segment. Inclusion of more than a few dozen covariates causes the log likelihood function to be numerically unstable such that convergence cannot be achieved. We narrow the covariates down to a set of 30 that include standard demographic variables (e.g., household size, age, income, education), utilization variables (commute distance, home parking location), and attitudinal variables (e.g., political and environmental attitudes). Although the latent class model with this large set of covariates converges using maximum likelihood estimation, estimates are fragile (numerical derivatives are approximate due to flat and/or discontinuous regions of the maximum likelihood function) and many of the estimated parameters are statistically insignificant.

Using the fragile, unstable model as a starting point, we remove variables one at a time from the set of controls and then re-estimate the model. Each iteration, we remove the variable that is the least statistically significant (with the highest p-value). We continue iterating as long as removing an additional covariate results in a decrease in the AIC and BIC, suggesting improved model fit. When 12 covariates remain, estimates become more stable. Table 7 displays the estimates for the preferred set of 8 covariates, which has the minimum AIC[20] of the iterative process.

The top panel of Table 7 shows the charging attribute preferences estimated separately for each of the five segments, the middle panel shows corresponding willingness to pay estimates, and the bottom panel shows how respondent characteristics impact segment membership probabilities. Segments one and three do not have a statistically significant preference for or against the status quo option of refueling with gasoline. Segment four has a highly significant positive preference for the status quo, while segments two and five have a highly significant negative preference for the status quo, preferring instead to recharge. Refuel time and refuel cost coefficients tend to be significant and negative as expected in most cases, however, the refuel time coefficient for segment three is positive and significant, though very small.

In the mixed logit (Table 5) WTP per minute reduction in refuel time is \$0.10 per minute. The implied value of time of \$6 per hour is low relative to other studies.[21] However, as shown in the middle panel of Table 7, segments two and four, which account for nearly half of respondents, have a WTP of \$0.50 and \$0.31 per minute, or \$30 and \$18.6 per hour, respectively. These values are more in line with the literature and with hourly wage rates. The WTP for segment 1 is low, \$0.04 per minute, or \$2.4 per hour. The older the respondent, the more likely he or she is to be in this segment. Thus, the low WTP may be driven by retirees.

The bottom panel of Table 7 shows the segment membership determinants. As mentioned above, the older the respondent, the more likely he or she is to belong to segment

[20] BIC is slightly smaller with fewer covariates, but this requires removing from the control set variables with highly significant coefficients.

[21] There has been little work on the strategic incentives faced by a respondent asked a multinomial forced choice question without a no purchase alternative. Because making an alternative available with a price higher than the respondent is willing to pay can provide no additional utility, any bias in the willingness to pay estimates would appear to be downward. Similar to all multinomial choice questions, more complex patterns of strategic behavior across different types of alternatives cannot be ruled out as these depend on perceptions of how many alternatives will be supplied and the beliefs of other people, with convergence to truthful preference revelation occurring when only one of the alternatives will not be supplied and/or uninformative priors about the beliefs of other people are held by the respondent.

Table 7 Charging scenarios: latent class model

	(1) Segment 1	(2) Segment 2	(3) Segment 3	(4) Segment 4	(5) Segment 5
Segment preferences					
Status quo	0.228	− 1.070***	− 0.748	0.681***	− 1.301***
	(0.209)	(0.382)	(0.941)	(0.184)	(0.346)
Refuel time	− 0.0379***	− 0.140***	0.00873**	− 0.431***	− 0.00241
	(0.00419)	(0.0319)	(0.00407)	(0.0600)	(0.00358)
Refuel cost	− 0.888***	− 0.279*	− 0.830***	− 1.378***	0.00231
	(0.0936)	(0.142)	(0.241)	(0.196)	(0.0763)
Willingness to pay					
Status quo		-$3.84		$0.49	
Per minute reduction in refuel time	$0.04	$0.50	-$0.01	$0.31	
Segment membership					
Age	0.0521***	0.0264	0.0252*	0.0506***	0.000
	(0.0127)	(0.0163)	(0.0129)	(0.0113)	
Income > $100k	0.324	0.601	0.455	0.973***	0.000
	(0.421)	(0.502)	(0.410)	(0.340)	
Body small†	− 1.006***	− 0.341	− 0.645*	− 0.643**	0.000
	(0.343)	(0.436)	(0.334)	(0.281)	
Married	− 1.023***	− 0.194	− 0.678*	− 0.502*	0.000
	(0.362)	(0.478)	(0.358)	(0.305)	
Race nonwhite	− 0.454	− 1.275**	− 0.394	− 0.655**	0.000
	(0.345)	(0.497)	(0.332)	(0.278)	
Attitude: air quality††	0.687***	0.634***	0.552***	0.512***	0.000
	(0.174)	(0.230)	(0.176)	(0.150)	
Attitude: enviro†††	− 0.228	− 0.0229	− 0.0716	− 0.448***	0.000
	(0.153)	(0.197)	(0.150)	(0.127)	
Liberal	0.435	1.416***	0.509	0.627*	0.000
	(0.421)	(0.502)	(0.402)	(0.346)	
Constant	− 1.782*	− 2.906**	− 1.606*	− 0.786	0.000
	(0.919)	(1.183)	(0.891)	(0.708)	
Share of respondents	23.4%	9.5%	14.6%	34.9%	17.6%

†Indicator variable for if the respondent indicated her most preferred body type for her next new vehicle purchase is a compact sedan, midsize sedan, or hatchback

††"How would you rate the air quality around where you live relative to other places in CA" one is excellent, five is terrible

†††"How important are environmental issues to you personally" one is not important and five is extremely important

AIC 6512; BIC 6892

Standard errors in parentheses

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

one, which has no clear preference for the status quo and a relatively small WTP per minute reduction in refuel time. Married respondents are also less likely to be in this segment, as are respondents who believe the air quality near where they live is poor.

Segment two members have a strong preference for recharging and a relatively large WTP to reduce refuel time. Respondents who are white, believe local air quality is poor, and who are politically liberal leaning are more likely to be in this segment. This is the smallest segment, consisting of just under 10% of respondents.

Segment four has a clear preference for refueling with gasoline and a moderate value of time. Respondents with higher incomes and who indicate that environmental issues are important to them are less likely to be in this segment.

Segment five is the omitted category. Although this means there are no standard errors estimated for segment five membership determinants, relative to other segments' coefficients, we can infer that younger respondents to whom environmental issues are important are more likely to be in this segment. These respondents have a strong proclivity to recharge rather than refuel with gasoline, and do not have clear strong preferences for refuel time or cost.

Statistically significant membership coefficients for segment three mostly fall in the middle of those of other segments, so there is less we can infer about segment three membership. These individuals have no clear preference for the status quo, and while moderately price sensitive, they have a very small (one cent) but negative WTP per minute reduction in refuel time. This is somewhat puzzling, essentially suggesting a zero value of time. This segment is the second smallest, consisting of 14.6% of respondents.

Overall, nearly 30% of respondents (segments two and five) have a strong preference for recharging, while 35% (segment 4) have a strong preference for refueling, and the remaining respondents do not have a strong preference for one or the other. Although 38% (segments one and three) of respondents have a very low value of time, around 45% (segments two and four) have a larger value of time and are willing to pay between \$0.31 and \$0.50 per minute reduction in refuel time. While the 35% of respondents are less likely to recharge, a larger portion of respondents are inclined towards recharging and/or would be open to recharge.

6 Conclusion

Understanding driver preferences for green refueling infrastructure is critical to more efficiently making public investments to expand its availability. Our results confirm that refueling convenience is a highly important attribute to consumers who intend to purchase a new vehicle. On average, drivers state that they prefer moderately risk-avoiding refueling practices for their gasoline vehicles, which are very similar to their refueling preferences for battery electric vehicles.

In this paper, we provide the first-of-its-kind estimates of drivers' willingness to pay to access location-specific charging stations and their willingness to accept longer wait times. Prospective PEV drivers are willing to pay \$0.04–\$0.05 per electric mile, similar to the actual variable cost of \$0.046 per electric mile of recharging at public charging stations in most utility service territories. Drivers are willing to pay to cover significant fixed costs at select locations; these include an average willingness to pay of \$1.59–\$3.15 for workplace Level 2 charging (when they are employees), \$1.43–\$2.81 for Level 2 grocery store access, \$0.58-\$1.65 for Level 2 mall access, \$0.54–\$1.38 for quick charging access near their homes, and \$0.68–\$1.26 for quick charging access along freeways.

Within our sample, our mean driver revealed that she would accept about \$0.10 per minute of wait time while refueling. Within a latent class analysis that identified five distinct consumer classes, consumers required payment for waiting for green charging that varied from a low of −$–.01–$0.04 for 25% of our sample up to $0.31 and $0.50 for 35% and 10% of our sample, respectively.

Although the 10% of respondents in segment two have the largest WTP to reduce refuel time, they have a strong preference towards recharging. Assuming refuel costs are equivalent between gasoline and electricity, they would be willing to wait 7 to 8 minutes longer to recharge ($3.84 ÷ $0.50). The 28% of respondents in segments one and three who do not have a strong preference for refueling with gasoline versus recharging have low values of time, suggesting for a moderate discount, they would no mind waiting longer to recharge versus refuel. While we cannot infer how segment five trades off cost versus time, these respondents also have a strong preference for recharging that suggests that would be willing to pay a premium and/or wait longer to recharge than refuel with gasoline.

Appendix

See Tables 8 and 9.

Table 8 UCLA new car buyer survey population†

	Caltrans survey, full population, weighted population (%)	Caltrans survey, new car buyers, weighted population (%)	UCLA new car buyer survey, weighted population (%)
Household size			
1 person	24.5	16.3	13.2
2 people	30.0	30.2	33.5
3 people	16.4	18.7	19.8
More than or equal to 4 people	29.1	34.9	33.4
Number of household vehicles			
None	8.0	3.7	2.8
1	32.7	26.3	29.6
2	37.2	42.9	42.3
More than or equal to 3 vehicles	22.0	27.2	25.3
Ethnicity			
White	68.7	75	75.3
African American	4.4	4	6.5
Multi-Racial	7.1	3	1.5
Other	19.8	18.6	16.8
Household ownership			
Own	72.2	76.8	62.0
Rent	27.6	23.0	35.0
Other	0.1	0.0	2.9
Income			
< 10k	5.6	2.9	5.1
10–25k	16.2	9.8	7.6
25k–35k	10.4	7.4	7.7

Table 8 (continued)

	Caltrans survey, full population, weighted population (%)	Caltrans survey, new car buyers, weighted population (%)	UCLA new car buyer survey, weighted population (%)
35k–50k	13.6	11.7	9.4
50k–75k	15.9	16.1	16.9
75k–100k	12.8	15.2	22.5
100k–150k	11.9	16.1	18.8
> 150k	13.6	21.0	12.1
Drivers in household			
None	4.9	1.6	0.3
1	30.9	23.2	19.4
2	45.2	50.9	51.1
3	13.9	17.4	16.3
More than or equal to 4 drivers	5.2	6.8	6.8
Sex			
Male	48.2	49.1	51.3
Female	51.8	50.7	48.5
Age			
Under 18	24.2	0.1	0.0
18–24	10.2	2.0	16.2
25–54	38.5	50.8	58.0
55–64	10.7	27.7	14.0
65 or over	16.5	19.4	10.2
Employment			
Employed	54.0	66.7	63.3
Unemployed	46.0	32.9	36.7
Household type			
Single family, detached	69.2	74.9	64.9
Single family, attached	7.8	7.3	9.9
Mobile Home	3.3	1.9	2.6
Building with 2 or more apartments	19.5	15.7	22.2
Boat, RV, Van, etc.	0.0	0.0	0.2
Education			
Not a high school graduate, 12 grade or less	7.4	3.4	7.1
High school graduate	14.8	11.0	24.7
Some college credit but no degree	18.7	18.1	23.2
Associate or technical school degree	11.4	11.0	10.6
Bachelor's or undergraduate degree	26.2	30.4	21.0
Graduate or professional degree	21.4	26.0	13.2

†Compared to Caltrans (2013) California 2010–2012 Household Travel Survey

Table 9 Definition of variables

Variable name	Description
Refuel time	Choice experiment attribute: refueling time (minutes)
Refuel cost	Choice experiment attribute: recharging/refueling cost ($/gal or $/gal equivalent)
Extra miles	Choice experiment attribute: Extra miles from charge
Work	Choice experiment attribute: charging available at workplace
Transit	Choice experiment attribute: charging available at parking facility at bus, train, or metro stop
Gym	Choice experiment attribute: charging available at gym, sport club or playing field
Mall	Choice experiment attribute: charging available at mall or retail outlet
Quick near home	Choice experiment attribute: charging available at quick charge station near home
Quick near freeway	Choice experiment attribute: charging available at quick charge station near freeway
Grocery	Choice experiment attribute: charging available at grocery store
School	Choice experiment attribute: charging available at school or daycare
Entertainment	Choice experiment attribute: charging available at movie theater or sporting arena
Employed	Indicator variable for if a respondent's current employment status is a paid employee or self-employed
Student	Indicator variable for if a respondent is a full or part time student
HOV access	Indicator variable for if HOV access is the first or second factor that would make the respondent more likely to purchase a PEV out of: free single-occupant high occupancy vehicle (HOV) access, quick charge stations near commute, quick charge stations on freeways for long trips, workplace charging, or charging charging at mall or grocery store
Quick charging near commute	Indicator variable for if quick charge stations near commute is the first or second factor that would make the respondent more likely o purchase a PEV out: free single-occupant high occupancy vehicle (HOV) access, quick charge stations near commute, quick charge stations on freeways for long trips, workplace charging, or charging at mall or grocery store
Quick charging near freeways	Indicator variable for if quick charge stations near freeways is the first or second factor that would make the respondent more likely o purchase a PEV out: free single-occupant high occupancy vehicle (HOV) access, quick charge stations near commute, quick charge stations on freeways for long trips, workplace charging, or charging at mall or grocery store
Workplace charging	Indicator variable for if workplace charging is the first or second factor that would make the respondent more likely to purchase a PEV out of: free single-occupant high occupancy vehicle (HOV) access, quick charge stations near commute, quick charge stations on freeways for long trips, workplace charging, or charging at mall or grocery store
Age	Respondent's age, in years
Income > $100k	Indicator variable for if respondent's household income exceeds $100,000
Body Small	Indicator variable for if the respondent indicated her most preferred body type for her next new vehicle purchase is a compact sedan, midsize sedan, or hatchback
Married	Indicator variable for if the respondent is married
Race nonwhite	Indicator variable for if the respondent's race is non-white

Table 9 (continued)

Variable name	Description
Attitude: air quality	Respondent's answer on a scale of one to five, where one is excellent and five is terrible, to 'how would you rate the air quality around where you live relative to other places in CA"
Attitude: enviro	Respondent's answer on a scale of one to five, where one is not important and five is extremely important, to 'how important are environmental issues to you personally"
Liberal	Indicator variable for if the respondent identified her political ideology as liberal (rather than conservative or moderate)

References

Achtnicht M, Georg B, Hermeling C (2012) The impact of fuel availability on demand for alternative-fuel vehicles. Transp Res Part D: Transp Environ 17(3):262–269

Bozdogan H (1987) ICOMP: a new model-selection criterion. In: 1. Conference of the international federation of classification societies, pp 599–608

Brownstone D, Bunch DS, Train K (2000) Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles. Transp Res Part B: Methodol 34(5):315–338

Bunch DS, Bradley M, Golob TF, Kitamura R, Occhiuzzo GP (1993) Demand for clean-fuel vehicles in California: a discrete-choice stated preference pilot project. Transp Res Part A: Policy Pract 27(3):237–253

California Department of Transportation (Caltrans) (2013) California household travel survey final survey report

Chen TD, Kockelman KM, Kahn M (2013) The electric vehicle charging station location problem: a parking-based assessment method for Seattle. Transp Res Rec 1254(28–36):2013

DeShazo JR, Song CC, Sinn M, Gariffo T (2015) State of the states' plug-in electric vehicle policies, UCLA Luskin Center Report

Eisel M, Schmidt J, Kolbe LM (2014) Finding suitable locations for charging stations: implementation of customers' preferences in an allocation problem. In: IEEE international electric vehicle conference (IEVC), Florence, pp 1–8

Ewing G, Emine S (2000) Assessing consumer preferences for clean-fuel vehicles: a discrete choice experiment. J Public Policy Mark 19(1):106–118

Franke T, Neumann I, Bühler F, Cocron P, Krems JF (2012) Experiencing range in an electric vehicle: understanding psychological barriers. Appl Psychol: Int Rev 61:368–391

Golob Thomas F, Bunch David S, David B (1997) A vehicle use forecasting model based on revealed and stated vehicle type choice and utilisation data. J Transp Econ Policy 1997:69–92

Hidrue MK, George RP, Willett K, Meryl PG (2011) Willingness to pay for electric vehicles and their attributes. Res Energy Econ 33(3):686–705

Ito N, Kenji T, Shunsuke M (2013) Willingness-to-pay for infrastructure investments for alternative fuel vehicles. Transp Res Part D: Transp Environ 18:1–8

Jia L, Hu Z, Liang W, Tang W, Song Y (2014) A novel approach for urban electric vehicle charging facility planning considering combination of slow and fast charging. In: International conference on power system technology (POWERCON), Chengdu, pp 3354–3360

Kitamura M, Hagiwara Y (2010) Honda 'lacks confidence' in electric-car demand. Bloomberg.com. http://www.bloomberg.com/apps/news?pid=newsarchive&sid=a_kxOOLkD.cU. Accessed 5 May 2017

Kurani KS, Thomas T, Daniel S (1996) Testing electric vehicle demand in 'hybrid households' using a reflexive survey. Transp ResPart D 1(2):131–150

Li S, Lang T, Jianwei X, Yiyi Z (2017) The market for electric vehicles: indirect network effects and policy design. J Assoc Environ Res Econ 4(1):89–133

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

Nylund KL, Tihomir A, Muthén BO (2007) Deciding on the number of classes in latent class analysis and growth mixture modeling: a Monte Carlo simulation study. Struct Equ Model 14(4):535–569

Potoglou D, Kanaroglou PS (2007) Household demand and willingness to pay for clean vehicles. Transp Res Part D: Transp Environ 12(4):264–274

Qian L, Didier S (2011) Heterogeneous consumer preferences for alternative fuel cars in China. Transp Res Part D: Transp Environ 16(8):607–613
Revelt D, Train K (1999) Customer-specific taste parameters and mixed logit. In: Working Paper. University of California, Berkeley
Scasny M, Zverinova I, Czajkowski M (2015) Individual preference for the alternative fuel vehicles and their attributes in Poland. No 8575, EcoMod2015, EcoMod. https://EconPapers.repec.org/RePEc:ekd:008007:8575. Accessed 5 May 2017
Scarpa R, Rose JM (2008) Design efficiency for non-market valuation with choice modelling: how to measure it, what to report and why. Aust J Agric Res Econ 52(3):253–282
Sheldon TL, DeShazo JR (2017) How does the presence of HOV lanes affect plug-in electric vehicle adoption in California? A generalized propensity score approach. J Environ Econ Manag 85:146–170
Sheldon TL, DeShazo JR, Carson RT (2017) Electric and plug-in hybrid vehicle demand: lessons for an emerging market. Econ Inq 55(2):695–713
Sweda T, Klabjan D (2011) An agent-based decision support system for electric vehicle charging infrastructure deployment. In: 7th IEEE vehicle power and propulsion conference, Illinois
Train KE (1998) Recreation demand models with taste differences over people. Land Econ 74(2):230–239
Williams B, DeShazo JR (2014) Pricing workplace charging: financial viability and fueling costs. In: Transportation Research Board 93rd annual meeting, no. 14-1137