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Research paper

Understanding the effects of vehicle portfolios on plug-in electric vehicles (PEVs)-adopting households' vehicle replacement decision: an application of vehicles transaction model

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ABSTRACT

Research on plug-in electric vehicles (PEVs) adoption to date has focused on understanding consumers' vehicle purchase decisions as single vehicle transactions. This research expands on this decision-making process by employing a vehicle transaction model to account for vehicle portfolio preferences at the household level. By leveraging discrete choice modeling techniques, specifically mixed multinomial logistic regression, we evaluate a sample of two-vehicle and PEV-adopting Californian households' vehicle transactions from 2017 to 2020. Our results demonstrate that there are strong complementarities among certain vehicle classes. Namely, PEV-adopting households are more likely to pair a car with a large truck or a SUV than with another car. Fuel type complementarities are also observed as households prefer to own a PEV and an internal combustion engine vehicle (ICEV) rather than a PEV-PEV portfolio. We also investigate households' income elasticity of choice for PEVs by quantifying their income sensitivity to the capital costs and operating costs of their vehicle portfolios. The implications of our work are two-fold: by applying the vehicle transaction model to empirical data, we estimate households' preference parameters for PEVs attributes and portfolios. These results contribute to the growing literature on the quantitative understanding of vehicle replacement decisions for PEV-adopting households. Our work also has implications for the projection of vehicle fleets, where understanding how households take vehicle portfolio complementarities into account is essential for future projections of vehicle fleets.

1. Introduction

In combating climate change, many governments around the world, including California, have set ambitious targets to electrify its transportation sector. In November 2022, California lawmakers passed the Advanced Clean Cars II Regulations (ACC II) which mandates that the sales of all new light-duty vehicles (LDVs) be zero-emissions by 2035 (CARB, 2022). This regulation would dramatically increase the supply of plug-in electric vehicles (PEVs) over the next decade and provide more choices to Californians in terms of vehicle makes and models. PEVs are defined as either battery electric vehicles (BEVs) or plug-in hybrid electric vehicles (PHEVs), and they are considered technological alternatives to internal combustion engine vehicles (ICEVs). Environmental benefits of PEVs manifest in the reduction of tailpipe greenhouse gasses (GHG) emissions and local criteria air pollutants during vehicles' drive cycles. In 2024, PEVs sales constitute about 24 % of the state's new light-duty vehicle sales, which is a small percentage compared to the target of 100 % by 2035 (CEC, 2025). A dramatic uptake of PEVs at the household level is expected over the next decade to reach the State's mandated target.

According to the 2017 National Household Travel Survey California Add-on, 37% of California households own two vehicles. On average, California households keep their vehicle for about 11 years, which implies that over the next decade, it is likely that two-vehicle California households would face the decision to replace one or more of their vehicles with PEVs (FHWA, 2017). On the other hand, given the policy directive from the ACC II, auto manufacturers have also pledged to increase their production of PEVs, offering a larger variety of PEVs in terms of vehicle classes, such as compact, subcompact, sports-utility vehicles (SUVs), trucks etc. (Consumer Reports, 2023). The increase in

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options of PEVs may incentivize households to adopt them. To capture the dynamics in households' vehicle replacement decisions, this research aims to understand how PEV-adopting households choose among different vehicle make-and-models and to quantify their preferences for vehicle portfolios. Furthermore, while under the policy backdrop of California's mandate to reach 100% zero-emissions vehicles (ZEVs) sales by 2035, it is crucial that we investigate consumer preferences for vehicle portfolios at the household level.

In this paper, we contribute to the literature on PEVs adoption, while addressing an important research gap in the existing literature: the lack of explicit consideration of the households' vehicle portfolios in their adoption decisions. We empirically estimate the effects of household vehicle portfolios on PEV-adopting households' vehicle replacement decision in our mixed multinomial logistic regression models. The quantification of households' preference parameters of vehicle portfolios serves as a unique contribution to the existing literature on PEV adoption and provides practical policy implications on the effectiveness of light-duty vehicle electrification policies, such as government mandated ZEVs sales targets. Furthermore, our work is well-situated to project future household vehicle fleet compositions in jurisdictions that have mandated the phase-out of ICEVs. By understanding how households value certain portfolios of vehicle attributes (e.g., fuel type and vehicle class), we can more accurately predict future fleet compositions under these policy mandates.

2. Literature review

Motivated by the desire to forecast vehicle demands, researchers have studied the topic of household vehicle choices extensively by leveraging the techniques of discrete choice modeling. The advantage of discrete choice modeling techniques lies in its ability to represent each household as a decision-making unit, which eliminates the reliance of assuming a representative consumer in an aggregate model. The results from a discrete choice model demonstrate the probability that a household would choose a certain vehicle out of all the available alternatives because the chosen alternative maximizes the utility to the household (Berkowitz et al., 1987). Early literature on this subject focused on two main categories of modeling: households' vehicle holdings (Manski & Sherman, 1977; Hensher & Le Plastrier, 1985; Berkowitz et al., 1987) and households' vehicle transactions (Hocherman et al., 1983, McCarthy, 1985). In our paper, we adopted the framework of a vehicle transaction model to explain households' vehicle replacement decision by leveraging data on their past vehicle transactions and sociodemographic variables (Hocherman et al., 1983). Methodologically, our model incorporated attributes of the purchased and replaced vehicles and households' sociodemographic data in a logistic regression to explicitly evaluate the influences of these factors on the vehicle replacement decisions.

With the increasing adoption of ZEVs, researchers applied vehicle transaction models to understand the demand for them because of their ability to forecast household vehicle stocks under different policy scenarios (Brownstone et al., 1996; Bunch et al., 1993). For instance, Brownstone et al. constructed a vehicle transaction model that leveraged both revealed preferences and stated preferences data on household vehicle choices and portfolios (Brownstone et al., 1996). To operationalize this, attributes of the replaced, the held, and the chosen vehicles all entered the model. For instance, net capital costs of the vehicle portfolio were computed by subtracting the depreciated market value of the replaced vehicle from the purchase price of the chosen vehicle, which we have also adopted in our model.

Since the early work on applying discrete choice modeling techniques to describe household vehicle transactions, a plethora of research has been conducted to advance the techniques of logistic regressions to more accurately capture the heterogeneous impacts of household sociodemographic on vehicle choices. For instance, Fatmi and Habib assessed the effects of life-cycle events on household vehicle ownership by accounting for repeated vehicle transaction decisions of the households (Fatmi & Habib, 2016). In another example, hypothesizing that first-time and transient (purchased a vehicle before) households may behave differently in terms of vehicle purchase decisions, Khan and Habib separately identified the effects of sociodemographic and life events on first-time and transient owners (Khan & Habib, 2021). Additionally, in evaluating the factors that influence household's decision on certain vehicle classes, they applied a mixed multinomial logit model to capture heterogeneity among households' preferences (Khan & Habib, 2021). To address the effects of heterogeneity in preferences among households on their vehicle choices, we also adopted a mixed multinomial logit model.

Besides refining the methodology of logistic regressions to explain households' vehicle choices, an important area of research in household vehicle choice modeling lies in data collection. Surveys are extremely important tools for collecting the required data for building vehicle choice models. Musti and Kockelman surveyed approximately 600 households in Austin, Texas to collect data on current, past vehicle holdings and use, and the intended future holdings (Musti & Kockelman, 2011). Similarly, Jensen et al. leveraged stated preference data on respondents' attitudes on vehicle attributes and charging infrastructures to investigate Danish households' preferences towards substituting ICEVs with PEVs of different vehicle classes (Jensen et al., 2021). Abovementioned research leveraged stated preference data collected via surveys to quantify households' preferences for certain vehicle attributes. While stated preference data is valuable, revealed preference data where vehicle transactions took place can enhance our understanding of households' preferences towards PEVs. In our study, we leveraged a survey method to collect revealed preference data which reflects household's actual vehicle replacement decisions.

In more recent literature, a study by Xing et al. investigated the emissions impacts of PEV adoption by estimating a random coefficients discrete choice model of new vehicle demand to identify the vehicles that PEVs are more likely to replace (Xing et al., 2021). By using survey data on households' chosen PEV, replaced vehicle, and their second-choice vehicle if they did not choose a PEV, the authors leveraged the preference heterogeneity among households' second-choice vehicles to more precisely estimate the random coefficients (Xing et al., 2021). In terms of substitutions between PEVs and ICEVs, Xing et al. found that about 80% of PEVs replaced fuel-efficient vehicles with an average fuel economy of 27 MPG (Xing et al., 2021). This result not only has implications for emissions reductions, but it also urges more research on how multi-car households choose PEV in consideration of the complementarity of their vehicles. The results from this paper are largely supported by the results from our work, which will be discussed in detail in the Results section.

To this end, we identified the research gap which our work intends to address: modeling the impacts of vehicle portfolios on two-vehicle households' decisions to replace one of their vehicles, conditional on their adopting a PEV. To our knowledge, two pieces of research have attempted to address part of the question of evaluating portfolio effects at the household fleet level as it relates to PEV adoption. Archsmith et al. evaluated how California households' choice of ICEV is influenced by the fuel economy of the replaced and the kept vehicle(s) by explicitly modeling vehicle portfolio effects at the household level (Archsmith et al., 2020). While Archsmith et al. accounted for household vehicle portfolio effects on vehicle adoption, the study was solely focused on ICEVs.

On the other hand, a working paper by Johansen and Munk-Nielson aims to achieve a similar objective to ours by investigating fuel type portfolio complementarities among Norwegian households via revealed preference data. Their work leverages discrete-continuous choice modeling techniques to account for both vehicle purchase choice and vehicle usage in order to quantify the portfolio effects on vehicle fuel type portfolios (Johansen & Munk-Nielsen, forthcoming). Johansen and Munk-Nielson leveraged vehicle registration data in Norway from 2005 to 2017 to study more than one million households, which would allow them to produce generalizable results on Norwegian households' vehicle portfolio complementarities. From their study, Johansen and Munk-Nielson found strong evidence on fuel type complementarity between PEV and ICEV. The results from their working paper are largely supported by the results from our work, which will be discussed in detail in the Results section.

3. Data

The main data source for this project is from the proprietary UC Davis PEVs Study, where the Electric Vehicles Research Center has surveyed approximately 10,500 PEV adopters in California from 2017 to 2020. The survey was distributed to applicants of the California Vehicle Rebate Project (CVRP), which means that the sampled households either purchased or leased a new PEV, since only new PEVs were eligible for the rebate during the study period. Furthermore, the CVRP implemented a MSRP cap of $60,000 on trucks, minivans, and SUVs, and a $45,000-cap on sedans, which took effect in February 2022 (Center for Sustainable Energy, 2023). This means that some luxury PEVs would not qualify for the rebate, such as Tesla Model 3, Tesla Model Y, and Tesla Model X. However, since our sample was collected before 2022, we observed households who adopted a wide range of PEVs, including the ones that have become ineligible due to the MSRP cap. In addition to the MSRP cap, the CVRP also implemented requirements on income eligibility. After February 2022, households were ineligible for the rebate if their household income was above $135,000 for single filers or $200,000 for joint filers (Center for Sustainable Energy, 2023). We adjusted the net capital costs of the sampled households' vehicle fleet based on the appropriate rebates that they received per the make-and-model of the PEV.

For our study, we focused on two-vehicle households from the dataset who replaced one of their vehicles with a PEV from 2017 to 2020, because these households constituted approximately 60 % of all surveyed households. For our study period, there were 6080 two-vehicle households in the sample. After cleaning the data, the sample has 4079 two-vehicle households. From the survey dataset, we identified these households' vehicle portfolio, including the vehicle that they chose to replace the PEV with and the vehicle that they kept. From there, we collected data on vehicle attributes of the replaced, the kept, and the chosen vehicle for each household at the year-make-and-model level (i.e., 2019 Honda Civic). In addition to the survey data, the main sources of vehicle attributes data came from the Fuel Economy Data on www.fueleconomy.gov and the DataOne VIN Decoder, which is an industry-leading software for providing vehicle-level attributes data. Table 1 below demonstrates the characteristics of these vehicles.

Figs. 1–3 demonstrate the distribution of sociodemographic

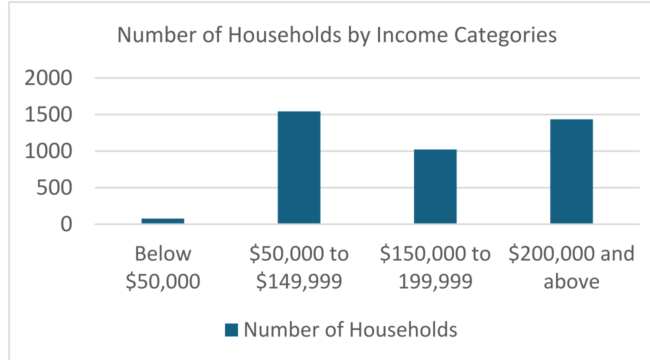

Fig. 1. The distribution of households by income categories. About 60 % of the households make an annual income of $150,000 and above.

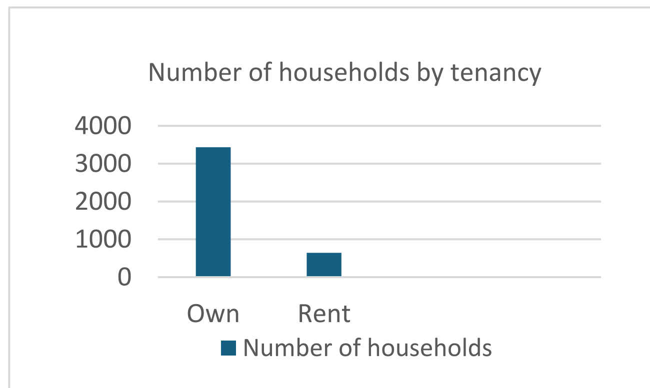

Fig. 2. About 84 % of the sampled households own their home.

variables: household income, tenancy, and level of education, respectively. We can see that these sampled households tend to be higher income, college educated, and property-owning. households.

After collecting the data, we conducted the following steps to process the data in order to obtain the variables of interest. First, from the fuel efficiency data, we computed the per mile operating costs for all vehicles. For BEVs, the operating cost (¢/mile) was computed by multiplying household electricity rates (¢/kWh) and the fuel economy of PEVs (kWh/mile). The households' electricity rates were collected from the websites of their corresponding utilities companies which the households provided in the survey. There were about 13 unique utilities companies in the sample, and the electricity rates range from 12¢/kWh

Table 1
Vehicle attributes summary statistics and data sources.

Vehicle Attributes	Replaced vehicle				Kept vehicle				Chosen vehicle				Data Sources
	Min	Max	Avg.	Std. deviation	Min	Max	Avg.	Std. deviation	Min	Max	Avg.	Std. deviation	
MSRP (1000's $)	10.1	121	31	12	8.6	447	35	16	27	102	45	16	DataOne VIN Decoder
Fuel efficiency (MPG/MPGe)	11	130	40	29.98	10	140	34	26.58	25	136	98	35.53	fueleconomy.gov
Vehicle age (years)	0	34	8	5.46	0	54	6	5.64	0	4	0.1	0.31	UC Davis PEVs Study
Vehicle class	**Vehicle class**			**Count**	**Vehicle class**			**Count**	**Vehicle class**			**Count**	fueleconomy.gov
	Cars			3044	Cars			1725	Cars			3056	
	SUV			877	SUV			1805	SUV			925	
	Trucks			70	Trucks			262	Trucks			0	
	Minivan			88	Minivan			287	Minivan			98	
Fuel type	**Fuel type**			**Count**	**Fuel type**			**Count**	**Fuel type**			**Count**	fueleconomy.gov
	BEV			565	BEV			383	BEV			2918	
	PHEV			383	PHEV			237	PHEV			1161	
	ICEV			3131	ICEV			3459	ICEV			0	

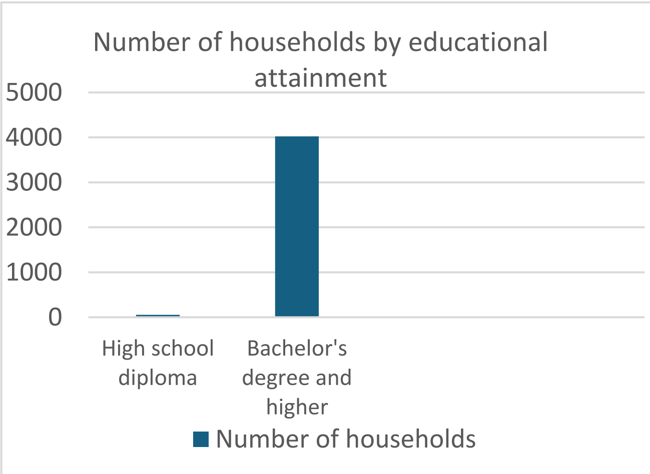

Fig. 3. Only 1 % of the sampled households do not hold a Bachelor's degree or higher.

to 44¢/kWh (See Fig. 4 below). For ICEVs, the operating cost was computed by multiplying the average annual gasoline prices in California for 2017, 2018, 2019, and 2020 ($/gallon) by the inverse of the ICEV's fuel economy ratings (gallons/mile). If the household purchased the vehicle in 2019, then the average California gasoline price of 2019 was used to compute the vehicle's operating costs. The gasoline price data was collected from the U.S. Energy Information Administration's historical database on average annual gasoline prices for each State (See Table 2 below). For PHEVs, we computed both the operating costs for the gasoline and electricity components by leveraging the utility factor of the PHEVs to determine the portion of the vehicle driving on electricity vs. gasoline. The utility factors data was collected from fueleconomy.gov.

In addition to the vehicle attributes, we constructed the following binary variables to capture the households' vehicle portfolios. Firstly, we identified the vehicle class of the two vehicles, then we constructed binary variables to explicitly represent all the chosen portfolios. To reduce the number of portfolios represented for computational reasons, we consolidated some vehicle classes into one category which resulted

Table 2
Average annual gasoline price in California from 2017 to 2020.

Year	Price ($/gallon)
2017	3.08
2018	3.55
2019	3.68
2020	3.13

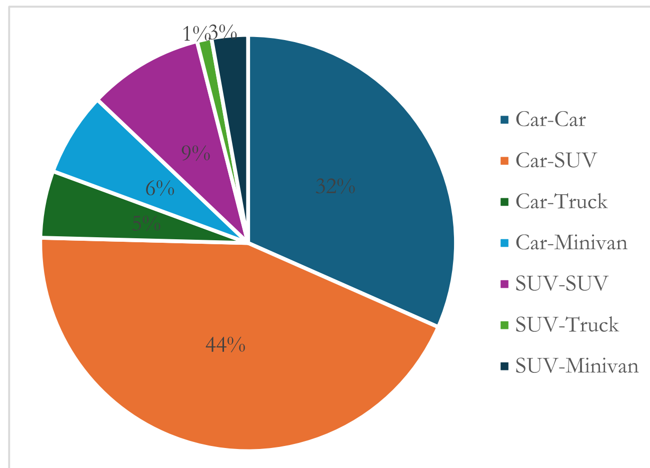

Fig. 5. Distribution of vehicle class portfolios among the sampled households. The most popular vehicle portfolio among PEV-adopting and two-vehicle households in the sample was "Car-SUV", followed by "Car-Car".

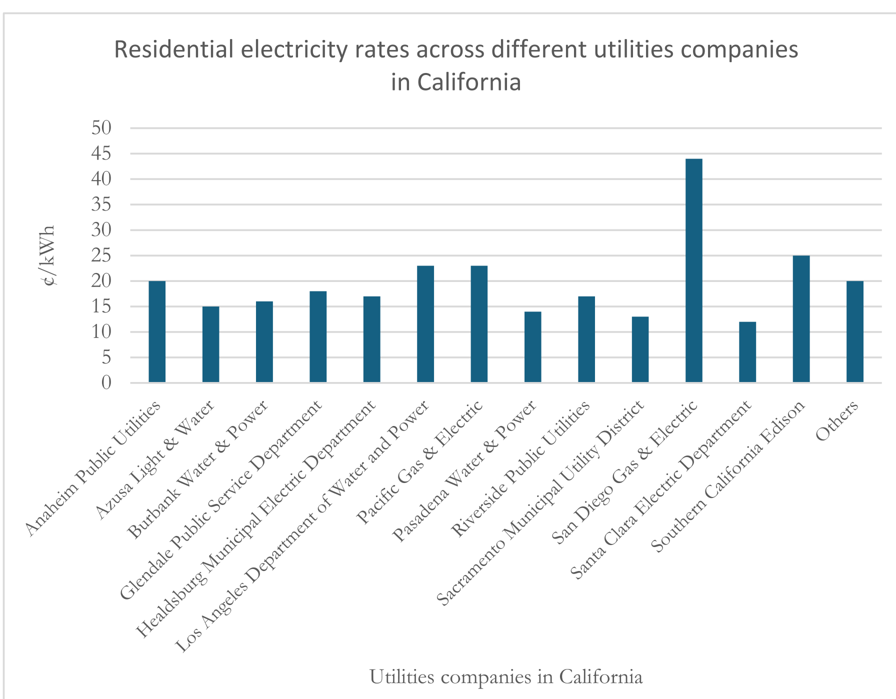

Fig. 4. Average retail electricity rate across multiple utilities companies in California in 2022. San Diego Gas and Electric company has the highest residential electricity rate at 44¢/kWh. Meanwhile, most of the utilities companies average around 20¢/kWh.

in four major categories: car, SUV, truck, and minivan. In addition, we constructed binary variables to reflect fuel type portfolios. Fig. 5 below demonstrates the distribution of household vehicle class portfolios, and Fig. 6 shows the distribution of household fuel type portfolios. Lastly, we constructed interaction variables that may influence households' PEV adoption decisions based on their socioeconomic data (Brownstone et al., 1996). Such variables include the interactions between household tenancy and education level and their adoption of BEVs vs. PHEVs. We also separately identified the effect of households' previous ownership of a luxury vehicle on their likelihood of adopting a BEV vs. a PHEV.

4. Method

In choice theories, a choice is viewed as an outcome of a sequential decision-making process that includes the following steps: 1) definition of the choice problem, 2) generation of alternatives, and 3) evaluation of the alternatives (Ben-Akiva & Lerman, 1985). To operationalize this process, it is important to capture these steps in the models and to reflect them as closely to reality as possible. In terms of defining the choice problem, identifying the level of decision making and the choice set are crucial components in the first and second steps, respectively. In our case, we modeled vehicle replacement choice conditional on households adopting a PEV. This introduces sample restriction in our model, in which we are unable to observe the vehicle replacement decisions of households which do not adopt any PEVs. The implication of such sample restriction is discussed in more detail in the Discussion section.

In terms of evaluating the choice alternatives, we center our analysis on random utility theory in the field of microeconomics. According to random utility theory, individuals choose the alternative from a choice set (C_n) that maximizes their utility. However, the utility that individuals gain from their choices are unobservable to the researchers due to potentially unobservable attributes of the alternatives, unobservable taste variations among individuals, and measurement errors. Therefore, the utilities are treated as random variables and are specified in the model as the probability of alternative i being chosen is equal to the probability that the utility of alternative i, U_i , is greater than or equal to the utilities of all other alternatives in the choice set (Ben-Akiva & Lerman, 1985).

$$P(i|C_n) = \Pr\left[U_i \geq U_j, all\ j \in C_n\right] \tag{2}$$

This approach allows us to derive the probability of each alternative being chosen by the individual by assuming a joint probability distribution for the set of random utilities. The specification of the utility function is broken down into two components: the deterministic (S_i) and the random components (z_i). The deterministic component of the utility function is specified by the vector of attributes of the alternative (V_i). In our model, we included attributes of the household vehicle portfolios, such as capital costs, operating costs, fuel type portfolios, and the vehicle class portfolios. Household sociodemographic variables are also included, such as tenancy, income, and level of education, to account for taste variations among households. The deterministic component of the utility function in our model is linear in parameters. On the other hand, the random component of the model refers to the error terms of the utility functions' specification, which we assume to be independently and identically Gumbel distributed (Ben-Akiva & Lerman, 1985).

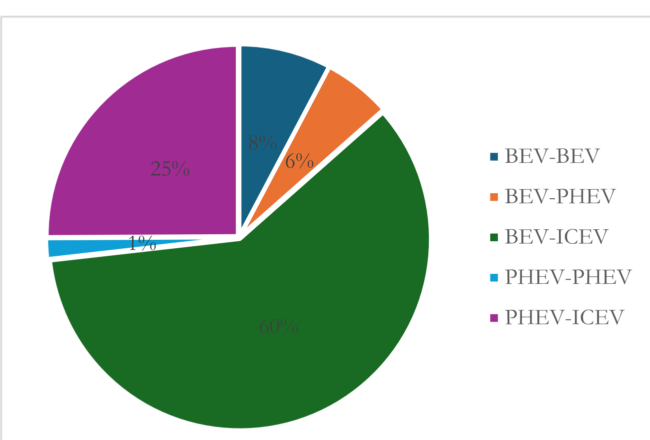

Fig. 6. Distribution of fuel type portfolios among the sampled households. The most popular vehicle fuel type portfolio is "BEV-ICEV", followed by "PHEV-ICEV".

$$U_i = V(z_i, S_i) + \varepsilon(z_i, S_i) = V_i + \varepsilon_i \tag{3}$$

Gumbel distribution of the error terms have desirable properties when applied to a multinomial logit model. Namely, based on the property: the difference between two independently Gumbel distributed error terms is logistically distributed, which helps derive the multinomial logit (Ben-Akiva & Lerman, 1985). The estimated multinomial logits have many useful applications in microeconomics. Specifically, we derive the income choice elasticities of PEV adoption for these sampled households. In terms of model estimation, we apply maximum likelihood estimation to solve for the parameters of the modeled attributes in order to maximize the probabilistic random utility functions (Ben-Akiva & Lerman, 1985).

4.1. Multinomial logit model

Our first model specification is a multinomial logit model to estimate the households' likelihood of replacing one of their vehicles, conditional on their choosing one of the 40 PEV make-and-models in our dataset. The observed array of PEVs represented approximately 57% of all available PEV make-and-models during the study period in the United States (U.S. Department of Energy, 2023). It is important to note that we create different choices for the same PEV make-and-models which underwent generational changes during the study period. For instance, Nissan LEAF underwent a generational change with different vehicle attributes from 2018 to 2019. We capture this by separately creating two choices for "2017 and 2018 Nissan LEAF" and "2019 and 2020 Nissan LEAF". After identifying PEV make-and-models, we multiplied the 40 unique make-and-models of PEVs by two and incorporated 80 choice alternatives in the model in order to capture the hypothetical situation of the two-vehicle households replacing the vehicle that they decided to keep. The specification of the utility function follows closely from Brownstone et al.'s paper, where we define net capital cost as the difference between the chosen PEV's MSRP and the depreciated market value of the replaced vehicle (Brownstone et al., 1996). Similarly, net operating cost is the difference between per-mile operating costs of the chosen PEV and that of the replaced vehicle.

In the model specification below, we separately identify the characteristics of the chosen PEV and the replaced vehicle. 'i' indexes the chosen PEV, and 'j' indicates the replaced vehicle. F_{ij} is the fuel type portfolio associated with choosing vehicle i and replacing vehicle j. C_{ij} denotes the vehicle class portfolio of choosing vehicle i and replacing vehicle j. D_l represents demographic variables including college education dummy and home-ownership dummy variables. BEV_i and $PHEV_i$ are dummy variables representing BEV and PHEV, respectively. L_j indicates whether the replaced vehicle is a luxury vehicle.

$$\begin{aligned} V_{ijl} = {} & \alpha_i + \sum_{f \in F} \beta_f \{F_{ij} = f\} + \sum_{c \in C} \gamma_c \{C_{ij} = c\} + \lambda D_l BEV_i + \theta L_j BEV_i \\ & + \mu L_j PHEV_i + \beta_{ncc}\, NCC_{i-j} + \beta_{noc}\, NOC_{i-j} \end{aligned} \tag{4}$$

Because our choice space accounts for the hypothetical situation where households could have decided to replace the vehicle that they kept, the net capital cost is a proxy for the asset value of vehicles to the household. To illustrate this point, households face the decision to replace either their Vehicle A or Vehicle B, with Vehicle A being the newer and more valuable vehicle (i.e., higher market value at the time of transaction). If they decide to replace Vehicle A, they face a smaller net capital cost. However, that also means that in the hypothetical situation where they replaced Vehicle B, their net capital cost would be greater. Our specification captures this tradeoff that households make when they decide which vehicle to replace vs. which to keep.

To quantify the impact of vehicle portfolios on vehicle replacement choice, we explicitly include vehicle class and fuel type portfolios in the model specification. The model includes home ownership and college education binary variables to control for their impacts on households' likelihood of adopting BEVs, since we observe that the sampled households tend to own homes and have higher-education degrees. In addition, we include binary variables to indicate whether the households replaced a luxury vehicle with a PEV and its effect on their likelihood to adopt BEV and PHEV, respectively. The determination of whether a vehicle is luxury or not is based on its make. For instance, BMW, Mercedes-Benz, Jaguar, and Lexus etc. are considered luxury vehicles. Including sociodemographic variables and luxury vehicles' influence on PEV adoption can separately identify these variables' influences on vehicle replacement decision, while simultaneously preserving the dynamics that the net capital cost and net operating cost variables intend to capture.

4.2. Multinomial logit model with income elasticities of choice

In the second model specification, we evaluate how household income affects households' choice of PEV make-and-model, since household income is one of the important factors in influencing PEV adoption. We interact household income with net capital costs and net operating costs. The specification of the income interaction follows from Axhausen et al.'s paper, where the interaction terms were continuous rather than segmented levels (Axhausen et al., 2008). The advantage of estimating a continuous interaction is the increased flexibility of our specification by avoiding having to assume segmentations by income levels. For instance, the income interaction terms in our second model specification take the following exponential form, where λ^{inc} represents the income sensitivity of the variables of interest (e.g., net capital costs and net operating costs) to changes in household income. This specification allows us to estimate the sampled households' income elasticities of choice, at the average household income level.

Table 3
Estimated coefficients of vehicle class portfolios, fuel type portfolios, and household sociodemographic variables on household choice of PEV make-and-models.

	(1)	(2)	(3)	(4)	(5)	(6)
Portfolio: car-car	NA	NA	NA	NA	NA	NA
Portfolio: car-SUV	0.68 (11.22) ***	0.68 (11.24) ***	1.38 (9.99) ***	NA	NA	NA
Portfolio: car-truck	1.83 (9.67) ***	1.82 (9.64) ***	2.98 (7.65) ***	NA	NA	NA
Portfolio: car-minivan	1.82 (10.29) ***	1.82 (10.32) ***	3.07 (6.88) ***	NA	NA	NA
Portfolio: SUV-SUV	2.53 (13.83) ***	2.53 (13.85) ***	1.91 (7.87) ***	NA	NA	NA
Portfolio: SUV-truck	3.30 (10.03) ***	3.30 (10.03) ***	4.16 (5.03) ***	NA	NA	NA
Portfolio: SUV-minivan	2.94 (15.29) ***	2.95 (15.29) ***	2.69 (7.12) ***	NA	NA	NA
Portfolio: minivan-truck	4.72 (3.27) ***	4.72 (3.27) ***	3.70 (2.52) **	NA	NA	NA
Portfolio: minivan-minivan	0.72 (0.77)	0.71 (0.78)	−82.1 (−1.31)	NA	NA	NA
Portfolio: BEV-BEV	NA	NA	NA	NA	NA	NA
Portfolio: BEV-PHEV	0.64 (4.03) ***	0.65 (4.05) ***	0.56 (2.02) *	NA	NA	NA
Portfolio: BEV-ICEV	2.08 (16.65) ***	2.09 (16.65) ***	3.12 (8.82) ***	NA	NA	NA
Portfolio: PHEV-PHEV	0.49 (1.81) *	0.51 (1.86) *	0.43 (0.78)	NA	NA	NA
Portfolio: PHEV-ICEV	2.37 (9.97) ***	2.37 (9.93) ***	2.93 (4.68) ***	NA	NA	NA
Net capital cost	0.10 (22.81) ***	0.10 (22.66) ***	NA	0.08 (25.1) ***	0.08 (24.9) ***	NA
Net capital cost mean [standard deviation]	NA	NA	−8.93 [1.21]	NA	NA	−9.63 [0.77]
Income elasticity wrt. net capital cost	NA	0.12 (1.53)	NA	NA	0.15 (1.74)	NA
Net operating cost	0.94 (1.08)	0.89 (1.00)	NA	0.12 (17.3) ***	0.12 (16.7) ***	NA
Net operating cost mean [standard deviation]	NA	NA	−9.86 [8.16]	NA	NA	−9.39 [0.01]
Income elasticity wrt. net operating cost	NA	0.08 (0.08)	NA	NA	0.09 (0.72)	NA
Home ownership on BEV adoption	6.19 (5.89) ***	6.18 (5.89) ***	6.13 (5.24) ***	8.71 (8.55) ***	8.73 (8.39) ***	8.68 (8.34) ***
College education on BEV adoption	6.25 (5.96) ***	6.25 (5.96) ***	6.21 (5.34) ***	8.94 (8.54) ***	8.91 (8.76) ***	8.91 (8.71) ***
Replaced a luxury vehicle on BEV adoption	0.51 (5.37) ***	0.51 (5.42) ***	0.38 (2.92) ***	0.65 (7.96) ***	0.66 (8.00) ***	0.32 (3.89) ***
Replaced a luxury vehicle on PHEV adoption	0.23 (1.55)	0.24 (1.62)	0.20 (0.98)	0.46 (3.40) ***	0.47 (3.45) ***	0.15 (1.05)
Alternative Specific Constants	X	X	X	X	X	X
Model Statistics						
AIC	19469.92	19470.15	19798.10	20642.61	20642.37	21015.13
BIC	19829.80	19842.66	20170.60	20926.71	20939.11	21311.87
Rho-squared	0.46	0.46	0.45	0.43	0.43	0.41

Note 1: Robust *t*-test statistics are included in "()"; standard deviations of random parameter are reported in "[]".
Note 2: "*" indicates 5 % significance level, "**" indicates 1 % significance level, and "***" indicates 0.5 % significance level.

$$V_{ijl} = \alpha_i + \ldots + \beta_{ncc}\left(\frac{inc_n}{\overline{inc}}\right)^{\lambda_{ncc}^{inc}} NCC_{i-j} + \beta_{noc}\left(\frac{inc_n}{\overline{inc}}\right)^{\lambda_{noc}^{inc}} NOC_{i-j} \tag{5}$$

4.3. Mixed multinomial logit model

To capture inter-household heterogeneity, we employ a mixed multinomial logit model which allows the estimated coefficients on net capital costs and net operating costs to have a distribution among the sampled households. We specify the random taste variation among households to have a lognormal distribution because of its desirable property of being non-negative. Each household's estimated coefficients on net capital costs (β_{ncc_n}) and net operating costs (β_{noc_n}) are therefore different from the population mean by some unobserved amount. Since there is no closed-form solution to the estimation of the random coefficients, Monte Carlo simulations are employed to approximate the value of random coefficients (Ben-Akiva & Lerman, 1985).

$$V_{ijl} = \alpha_i + \ldots + e^{(\overline{\beta}_{ncc} + \sigma_{ncc})} NCC_{i,-j} + e^{(\overline{\beta}_{noc} + \sigma_{noc})} NOC_{i,-j} \tag{6}$$

5. Results

In this section, we present the estimated parameters from six model specifications. The first three specifications in Table 3 demonstrate the estimated parameters from the multinomial logit model, followed by the multinomial logit model with income elasticities, and then the mixed multinomial logit model, respectively. The common parameters among these specifications are vehicle class portfolios, fuel type portfolios, interaction terms of household education and tenancy with BEV adoption, and interaction terms of previous ownership of luxury vehicles with BEV adoption. The model specification with income elasticities of choice added two more parameters: income elasticities of choice with respect to net capital cost and that with respect to net operating cost. Lastly, results from the mixed multinomial logit model presented the estimated means and standard deviations of the parameters of net capital cost and net operating costs. The latter three specifications (Specifications 4 to 6) estimated the naïve model without accounting for portfolio complementarities at the fuel type and vehicle class levels.

One of the key contributions of this paper is the explicit quantification of portfolio effects within the household vehicle fleets, at both the fuel type and vehicle class levels. This is an important contribution because it provides novel insights into how PEV-adopting households consider vehicle complementarities in their household vehicle fleets. To that end, the estimated parameters from the mixed multinomial logit model on the vehicle class portfolios reveal quantitative insights on households' preferences for them. For instance, the reference level for the vehicle class portfolios is "car-car", and relative to this portfolio, we observe that the estimated coefficients for the other vehicle class portfolios, except for "minivan-minivan", are positive and statistically significant. Furthermore, we observe that the estimated coefficients of portfolios of the same vehicle class (e.g., SUV-SUV, minivan-minivan) are less preferred to portfolios of different vehicle classes (e.g., car-truck, car-minivan, SUV-truck, and SUV-minivan, minivan-truck). This set of results not only implies that PEV-adopting households prefer to hold a fleet of different vehicle classes, but they also prefer holding onto larger vehicles. Since there are no plug-in electric trucks in our sample, we observe that households value holding onto their internal combustion engine trucks to complement their PEV. This further indicates that the sampled households highly prefer holding onto their internal combustion engine trucks, which has implications for future household fleet compositions in California, such as extending the lifetime of internal combustion engine trucks and driving relatively fuel-inefficinet vehicles. On the other hand, the increasing availability of plug-in electric trucks may impact household preferences which we discuss in detail later in the paper.

The results on the fuel type portfolios are aligned with our expectations and findings from Johansen and Munk-Nielson's forthcoming paper, where relative to the reference portfolio of "BEV-BEV", households prefer other portfolios with at least one car that is partly or fully fueled by gasoline or diesel. For instance, the estimated coefficient of the "BEV-ICEV" portfolio from the mixed multinomial logit model is the highest, relative to the reference fuel type portfolio: "BEV-BEV". Following the "BEV-ICEV" portfolio, the "PHEV-ICEV" portfolio is the second most preferred portfolio. Both results are consistent with our expectations and other literature on PEV adoption, where to mitigate potential range anxiety around driving BEVs, households prefer to complement their BEVs with a PHEV or an ICEV (Johansen & Munk-Nielsen, forthcoming).

When interpreting the estimated coefficients of net capital cost, we first discuss the interpretations of the estimated coefficients from the first and second model specifications. Both models yield an estimated coefficient of 0.10, which means that households are more likely to replace a vehicle that results in a large gap between the value of the chosen PEV and the replacement vehicle. In other words, PEV-adopting households are more likely to replace their lower-value and older vehicles. Furthermore, the fact that the average annual household income of the sampled household is \$181,000 indicates that this sample is skewed towards high-income households who are likely to own a valuable portfolio of vehicles. From the second model, we find that the households' income elasticity with respect to net capital cost of their fleet has a positive value of 0.12, but not statistically significant at 5 %. This lack of statistical significance may be due to the sample being heavily skewed towards high-income households, and therefore the sample lacks variation among households' income sensitivity to changes in the value of their vehicle fleets.

Interpreting the estimates of the mean and standard deviation of net capital costs from the mixed multinomial logit model requires transformations such that the estimated mean is given by: $E[\beta_{ncc}] = e^{\left(\overline{\beta}_{ncc} + \frac{1}{2}\sigma_{ncc}^2\right)}$. The estimated mean of net capital costs is 0.28, which means that households are even more likely to replace their lower-value vehicle. The magnitude of this estimated coefficient on net capital costs is approximately 3 times greater than that from the first and two model specifications. By incorporating random variations among the sampled households' preferences for the value of their vehicle fleet, the estimated impact of this variable on households' likelihood of replacing an older and less-value vehicle increases. This indicates that when we account for the fact that individual households may have different preferences for the value of their vehicle fleet, we observe that they are much more likely to have a vehicle fleet of a higher value.

When it comes to the net operating cost, the sign of the estimated coefficients across the first two model specifications is positive but not statistically significant at the 5% level. Given that the estimated coefficients on net operating costs are not statistically different from zero, we deduce that the operating costs of their vehicle portfolios do not influence the sampled high-income households' vehicle replacement decision. One thing to note is that during the study period of 2017–2020, the average gasoline price in California was much lower at \$3.36/gallon than the average gasoline price in the following 4-year window: \$4.76/gallon (U.S. Energy Information Agency, 2025). This increase in gasoline prices would likely increase the households' sensitivity to operating costs.

Other results of interest include the effects that education level and home ownership have on households' likelihood of adopting a BEV vs. a PHEV. Households with college-level or higher education and households who own a home are more likely to adopt a BEV, which is consistent with findings from existing literature (Hardman et al., 2016, Tal et al., 2013). Homeownership is a significant determining factor in households' decision to adopt a BEV or not, since the ability to charge their BEV at home heavily influences the convenience factor of owning a BEV (Scorrano et al., 2020; Higgins et al., 2017). Lastly, we also included the effects of households' replacing a luxury vehicle on their adoption decision of BEVs and PHEVs. According to the results from the mixed multinomial logit model, households that replaced a luxury vehicle are 0.38 units more likely to adopt a BEV compared to those who did not replace a luxury vehicle. This finding indicates that BEVs are more likely to be viewed as luxury vehicles. Furthermore, it also points at the fact that luxury-vehicle-owning households may prefer replacing their luxury vehicle with a vehicle that exhibits similar status, which makes BEVs more preferred than PHEVs. This set of results are consistent with existing literature on the influence of luxury vehicle ownership and BEV adoption (Mohamed et al., 2018; Nazari et al., 2023). On the other hand, this effect was not statistically significant for households who adopted PHEVs.

We also test the influence of incorporating the fuel type and vehicle class portfolios on the performance of the first three model specifications by estimating three additional "naïve" model specifications without the portfolios. Specification 4, 5, and 6 demonstrate the results from these models. For model specifications 4 and 5, the results are non-intuitive. For instance, the estimated coefficients for net operating cost are positive and statistically significant, which indicates that PEV-adopting households are more likely to replace a fuel-efficient vehicle with a PEV. The estimated coefficients on the effects of households' replacing a luxury vehicle on their likelihood of choosing a PHEV in Specification 4 and 5 are positive and statistically significant, which are different from the results from Specification 1 and 2. When comparing the AIC and BIC between Specification 3 and 6, the naïve model underperforms by approximately 6%. By estimating the models without vehicle class and fuel type portfolios, we demonstrate the importance of incorporating them to produce intuitive estimated coefficients. Furthermore, the model performance also improved by incorporating the portfolios.

5.1. Counterfactual analysis

Lastly, we perform a counterfactual analysis by varying the vehicle class of the kept vehicle in the household portfolio to compute the changes in probabilities of the households replacing the vehicle that they decided to replace (i.e., Vehicle A). For instance, if a household holds a "car-car" portfolio, we simulated their changing the vehicle portfolio to "car-SUV" to compute the changes in probability of the household replacing one vehicle versus the other in their portfolio. We repeated this step for all possible vehicle class portfolios in the data set. Fig. 7 below shows the results of the counterfactual analysis. The column is faceted to represent the vehicle that the households decided to replace (i.e., Vehicle A), and the row is faceted to represent the PEV that the household chose. There is no PEV truck in our data, which is why the "truck" option is missing in the row of the figure. The combination of the faceted row and column represents the vehicle class portfolio that the households own.

As demonstrated, households which initially have a portfolio of "car-car" are more likely to replace Vehicle A when they decide to keep a larger vehicle (e.g., SUV, minivan and truck) in their portfolio. For households that have chosen to keep a larger vehicle with their car (e.g., car-SUV, car-minivan, and car-truck), they are less likely to replace Vehicle A if they decide to keep a smaller vehicle. For households which own a minivan as part of their portfolio, the probability of their replacing Vehicle A is close to unchanged among different counterfactual vehicle portfolio choices. Such results also apply to households which own a SUV, except for households which own a portfolio of "SUV-car". For these households, they are less likely to replace Vehicle A if they decide to keep a SUV instead of a car. This set of results indicates that Vehicle A is more likely to be a smaller and potentially more fuel-efficient vehicle, which is consistent with Xing et al.'s finding (Xing et al., 2021).

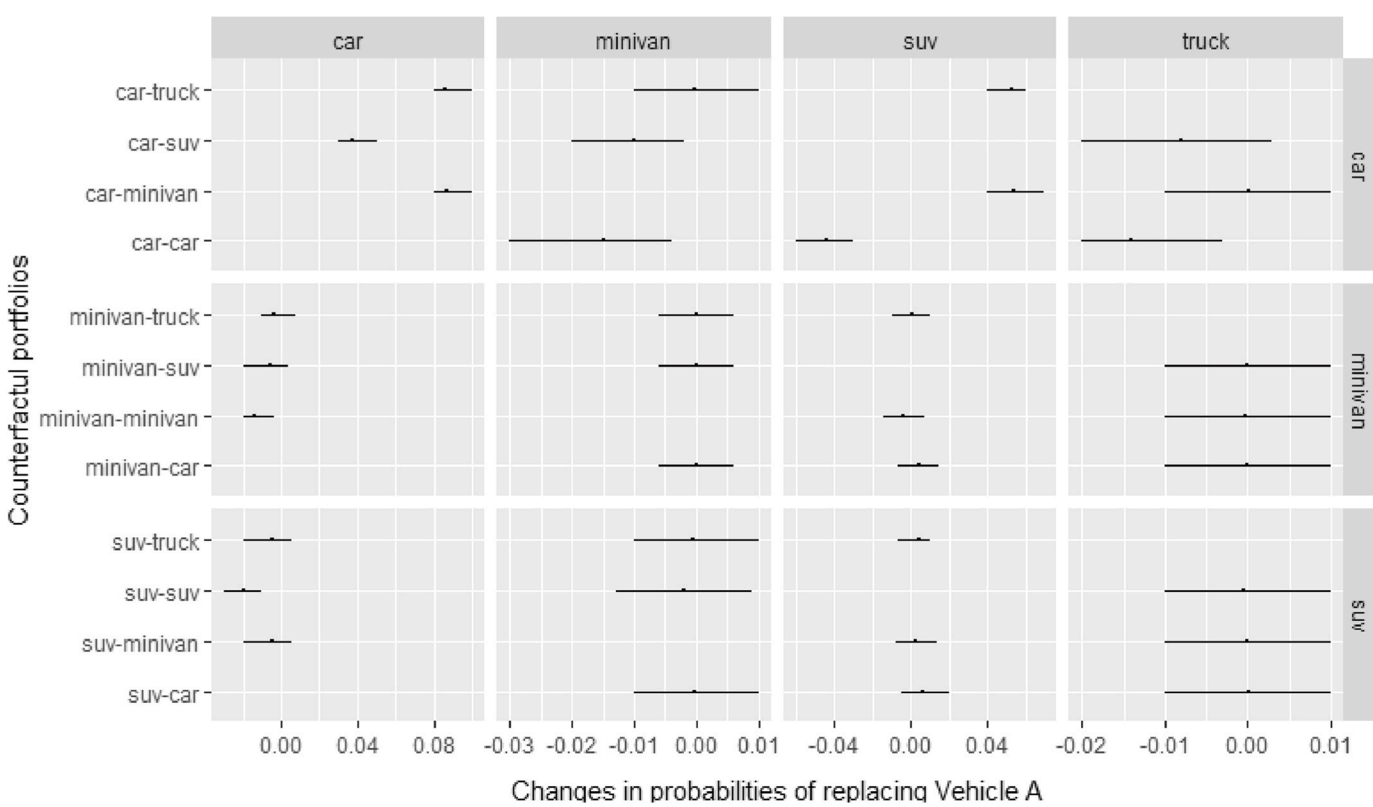

Fig. 7. Changes in probabilities of households replacing the vehicle that they decided to replace (i.e., Vehicle A) as they choose to keep vehicles of different vehicle class.

6. Discussion and conclusion

Overall, the results from our analysis demonstrate the importance of accounting for the effects of vehicle portfolios when understanding how PEV-adopting households choose which vehicle to replace. Portfolio complementarity at both the vehicle class and fuel type levels are important factors which households consider. Namely, we find that the sampled households prefer pairing a car with a larger vehicle, such as a minivan or a truck. This demonstrates the fact that vehicles from different classes serve different and complementary purposes in a household. Furthermore, it is important to note that there was no make-and-model of plug-in electric trucks available during the study period. The portfolio complementarity that we observed among "car-truck", "SUV-truck", and "minivan-truck" reflects the sampled households' preferences for pairing a PEV with an internal combustion engine truck. The fact that the sampled households highly value pairing an internal combustion engine truck with their PEV signals that trucks may be a difficult vehicle segment to electrify. As of 2021, plug-in electric trucks became available for sales in the United States. Future research should collect data on households who have adopted an electric truck and to understand the changes in preference parameters for vehicle class portfolios once the availability of plug-in electric trucks has increased.

On the front of methodological contributions, we accurately reflect the decision facing each sampled two-vehicle household when they replaced one of their vehicles with a PEV by leveraging a vehicle transaction model. Specifically, we model both the observed and the hypothetical replacements of a vehicle by a PEV among two-vehicle households. Furthermore, by explicitly quantifying the impacts that vehicle class and fuel type portfolios have on their decisions, our results address this knowledge gap and contribute to the growing literature on PEV adoption. Our sample restriction implies that only PEV-adopting households are observed, and the sample is skewed towards higher-income and college-educated households in California which compromised its representativeness. Future work should consider expanding the sample size by surveying both PEV-adopting and non-PEV-adopting households to understand the differences in preferences between these two groups of households. A more representative sample would improve the generalizability of our results.

In terms of policy implications, our results provide practical considerations for California's transportation electrification policies. As the State pushes towards electrifying its transportation sector to achieve its GHG reduction goals, it is important to consider how households' preferences for certain vehicle portfolios affect which vehicle they choose to electrify. Our results reveal that most of the sampled households choose a PEV from the "car" vehicle class and pair it with a larger vehicle (e.g., SUV, truck, minivan). This implies that two-vehicle households may prefer to electrify their car first, while holding onto a larger and more carbon-intensive ICEV. This trend would largely compromise the State's goal of reducing GHG emissions, and it warrants careful designs of market-based instruments to shift consumers' preferences for which vehicle in their household fleet to electrify. A potential solution would be to design financial incentives to lower the MSRP of electric trucks. As demonstrated by our work, accounting for how households value their vehicle fleet when making decisions on their PEV not only provides additional scholarly insights into their behaviors, but it is also an important area of consideration for policymaking.

Extending the policy implications beyond California, we consider countries where the PEV penetration rate is much higher than that of California. China is a global leader in PEV adoption. As of 2023, there are 22 million PEVs in China's LDV fleet, accounting for approximately 8% of its fleet (IEA, 2024; Shui et al., 2024). China's LDV fleet is undergoing a rapid transition from ICEVs to PEVs, given the aggressive sales of PEVs at 40% of all light-duty vehicle sales in 2024 (IEA, 2024). The wide adoption of PEVs in China can be explained by its cost competitiveness with ICEVs in the absence of government subsidies. The sales-weighted average price of PEVs reached parity with their ICEV counterparts in 2020 (IEA, 2024). Meanwhile, the adoption of large vehicle classes within PEVs is increasing; SUVs and trucks constituted 50% of all PEV sales in China in 2023 (IEA, 2024). This trend is even more pronounced in the United States, with larger vehicle classes constituting 75 % of all PEV sales in 2023 (IEA, 2024).

Based on the popularity of large vehicle classes within PEVs and accounting for our finding, we can reasonably assume that by increasing the make-and-model availability within these vehicle classes, PEV-adopting households who initially prefer to hold onto a larger and more carbon-intensive ICEV may replace their vehicle with a PEV SUV or truck. However, targeted policy can further incentivize and accelerate this process by potentially designing a trade-in program, where households who replace an ICEV truck or SUV with a PEV counterpart would receive a subsidy towards their PEV. Such program is in effect in China, where households who replace a fuel-inefficient vehicle with a PEV are eligible for up to about $2800 USD in rebate (China's Ministry of Commerce, 2025). The rebate amount constitutes of about 10% of average PEV purchase price in China (IEA, 2024). Such targeted approach sends the correct economic signals to incentivize the adoption of PEVs, while addressing the unintended consequences of households potentially holding onto fuel-inefficient and polluting vehicles for longer.

CRediT authorship contribution statement

Jean Y. Ji: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **David S. Bunch:** Validation, Supervision, Resources, Methodology, Conceptualization. **Alan Jenn:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

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References

Archsmith, J., Gillingham, K. T., Knittel, C. R., & Rapson, D. S. (2020). Attribute substitution in household vehicle portfolios. *The RAND Journal of Economics, 51*(4), 1162–1196. https://doi.org/10.1111/1756-2171.12353

Axhausen, K. W., Hess, S., König, A., Abay, G., Bates, J. J., & Bierlaire, M. (2008). Income and distance elasticities of values of travel time savings: New Swiss results. *Transport Policy, 15*(3), 173–185. https://doi.org/10.1016/j.tranpol.2008.02.001

Ben-Akiva, M., & Lerman, S. (1985). *Discrete choice analysis: Theory and application to Travel demand*. The MIT Press.

Berkowitz, M. K., Gallini, N. T., Miller, E. J., & Wolfe, R. A. (1987). Forecasting vehicle holdings and usage with a disaggregate choice model. *Journal of Forecasting, 6*(4), 249–269. https://doi.org/10.1002/for.3980060404

Brownstone, D., Bunch, D. S., Golob, T. F., & Ren, W. (1996). A transactions choice model for forecasting demand for alternative-fuel vehicles. *Research in Transportation Economics, 4*, 87–129. https://doi.org/10.1016/S0739-8859(96)80007-2
Bunch, D. S., Bradley, M., Golob, T. F., Kitamura, R., & Occhiuzzo, G. P. (1993). Demand for clean-fuel vehicles in California: A discrete-choice stated preference pilot project. *Transportation Research Part A: Policy and Practice, 27*(3), 237–253.
California Air Resources Board. (2022). Advanced clean cars II. https://ww2.arb.ca.gov/our-work/programs/advanced-clean-cars-program/advanced-clean-cars-ii.
California Energy Commission. (2025). New ZEV sales in California. https://www.energy.ca.gov/data-reports/energy-almanac/zero-emission-vehicle-and-infrastructure-statistics/new-zev-sales.
Center for Sustainable Energy. (2023). Eligibility and requirements. https://cleanvehiclerebate.org/en/eligibility-guidelines.
China's Ministry of Commerce. (2025). The old-for-new car exchange in 2025. https://www.gov.cn/zhengce/zhengceku/202501/content_6999564.htm.
Consumer Reports. (2023). Hot, new electric cars that are coming soon. https://www.consumerreports.org/cars/hybrids-evs/hot-new-electric-cars-are-coming-soon-a1000197429/.
Fatmi, M. R., & Habib, M. A. (2016). Longitudinal vehicle transaction model: Assessment of lead and lagged effects of longer-term changes and life-cycle events. *Transportation Research Record: Journal of the Transportation Research Board, 2566*(1), 11–21. https://doi.org/10.3141/2566-02
Federal Highway Administration. (2017). 2017 national household travel survey. https://nhts.ornl.gov.
Hardman, S., Shiu, E., & Steinberger-Wilckens, R. (2016). Comparing high-end and low-end early adopters of battery electric vehicles. *Transportation Research Part A: Policy and Practice, 88*, 40–57. https://doi.org/10.1016/j.tra.2016.03.010
Hensher, D. A., & Le Plastrier, V. (1985). Towards a dynamic discrete-choice model of household automobile fleet size and composition. *Transportation Research Part B: Methodological, 19*(6), 481–495. https://doi.org/10.1016/0191-2615(85)90043-8
Higgins, C. D., Mohamed, M., & Ferguson, M. R. (2017). Size matters: How vehicle body type affects consumer preferences for electric vehicles. *Transportation Research Part A: Policy and Practice, 100*, 182–201. https://doi.org/10.1016/j.tra.2017.04.014
Hocherman, I., Prashker, J. N., & Ben, M. (1983). Estimation and use of dynamic transaction models of automobile ownership. *Transportation Research Record, 944*, 134–141.
International Energy Agency. (2024). Global EV outlook 2024. https://iea.blob.core.windows.net/assets/a9e3544b-0b12-4e15-b407-65f5c8ce1b5f/GlobalEVOutlook2024.pdf.
Jensen, A. F., Thorhauge, M., Mabit, S. E., & Rich, J. (2021). Demand for plug-in electric vehicles across segments in the future vehicle market. *Transportation Research Part D: Transport and Environment, 98*, Article 102976. https://doi.org/10.1016/j.trd.2021.102976
Johansen, B. G., Munk Nielsen, A. (in press) Portfolio complementarities and electric vehicle adoption.].
Khan, N. A., & Habib, M. A. (2021). When do households make vehicle transactions? What type of vehicle households choose after transaction events? *Travel Behaviour and Society, 22*, 32–47. https://doi.org/10.1016/j.tbs.2020.08.002
Manski, C. F., & Sherman, L. (1977). Forecasting equilibrium motor vehicles holdings by means of disaggregate models. *Transportation Research Record, 764*, 96–103.
Mohamed, M., Higgins, C. D., Ferguson, M., & Réquia, W. J. (2018). The influence of vehicle body type in shaping behavioural intention to acquire electric vehicles: A multi-group structural equation approach. *Transportation Research Part A: Policy and Practice, 116*, 54–72. https://doi.org/10.1016/j.tra.2018.05.011
Musti, S., & Kockelman, K. M. (2011). Evolution of the household vehicle fleet: Anticipating fleet composition, PHEV adoption and GHG emissions in Austin, Texas. *Transportation Research Part A: Policy and Practice, 45*(8), 707–720. https://doi.org/10.1016/j.tra.2011.04.011
Nazari, F., Noruzoliaee, M., Mohammadian, A., & Kouros. (2023). Electric vehicle adoption behavior and vehicle transaction decision: Estimating an integrated choice model with latent variables on a retrospective vehicle survey. *Transportation Research Record: Journal of the Transportation Research Board*. https://doi.org/10.1177/03611981231184875, 03611981231184875.
Scorrano, M., Danielis, R., & Giansoldati, M. (2020). Dissecting the total cost of ownership of fully electric cars in Italy: The impact of annual distance travelled, home charging and urban driving. *Research in Transportation Economics, 80*, Article 100799. https://doi.org/10.1016/j.retrec.2019.100799
Shui, B., Shafique, M., & Luo, X. (2024). Light-duty passenger vehicle electrification in China from 2021 to 2050 and associated greenhouse gas emissions: A dynamic fleet perspective. *Transportation Research Part D: Transport and Environment, 130*, Article 104199. https://doi.org/10.1016/j.trd.2024.104199
U.S. Department of Energy. (2023). Alternative fuels data center. *Availability of electric vehicles*. https://afdc.energy.gov/vehicles/electric_availability.html.
U.S. Energy Information Agency. (2025). Weekly retail gasoline and diesel prices. https://www.eia.gov/dnav/pet/pet_pri_gnd_dcus_sca_a.htm.
Xing, J., Leard, B., & Li, S. (2021). What does an electric vehicle replace? *Journal of Environmental Economics and Management, 107*, Article 102432. https://doi.org/10.1016/j.jeem.2021.102432