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Role of Vehicle Technology on Use: Joint analysis of the choice of Plug-in Electric Vehicle ownership and miles traveled

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Role of Vehicle Technology on Use: Joint analysis of the choice of Plug-in Electric Vehicle ownership and miles traveled

September 2023

A Research Report from the National Center for Sustainable Transportation

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The increasing diversity of vehicle type holdings and growing demand for BEVs and PHEVs have serious policy implications for travel demand and air pollution. Consequently, it is important to accurately predict or estimate the preference for vehicle holdings of households as well as the vehicle miles traveled by vehicle body- and fuel-type to project future VMT changes and mobile source emission levels. Leveraging the 2019 California Vehicle Survey data, this report presents the application of a utility-based model for multiple discreteness that combines multiple vehicle types with usage in an integrated model, specifically the MDCEV model. The model results suggest the important effects of household demographics, residence location, and built environment factors on vehicle body type and powertrain choice and usage. Further the predictions associated with changes in built environment factors like population density can inform the design of land-use and transportation policies to influence household vehicle holdings and usage that can in turn impact travel demand and air quality issues in California.</td></tr>
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EXECUTIVE SUMMARY

The increasing diversity of vehicle type holdings and growing demand for battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) have serious policy implications for travel demand and air pollution. Consequently, it is important to accurately predict or estimate the preference for vehicle holdings of households as well as the vehicle miles traveled (VMT) by vehicle body- and fuel-type to project future VMT changes and mobile source emission levels. In past studies, there has been major discrepancy in the estimates of how much BEVs are being driven compared to ICEVs in a multi-vehicle household and thereby their likely contribution to emission reduction. All these prior studies on BEV usage are reduced-form models that do not consider vehicle choice and VMT in an integrated framework. VMT estimation conditional on choice of a vehicle may also suffer from endogeneity concerns; households who drive more may be more gasoline price sensitive. As a result, they may also prefer BEVs and PHEVs that offer cost savings. The current report presents the application of a utility-based model for multiple discreteness that combines multiple vehicle types with usage in an integrated model, specifically the multiple discrete continuous extreme value (MDCEV) model. We use the 2019 California Vehicle Survey data here that allows us to analyze the driving behavior associated with more recent plug-in electric vehicle (PEV) models (with potentially longer range). Here, PEVs include BEVs and PHEVs. Important findings from the model include:

- From the vehicle choice perspective, the MDCEV model suggests that on average households have an inherent preference for internal combustion engine vehicles (ICEVs) compared to EVs in the vehicle segments with all three powertrains (BEVs, PHEVs, and ICEVs).
- Considering vehicle usage, the MDCEV model suggest that when EVs of a certain body type exist in a household fleet, on average, households tend to reach satiation later for EVs than ICEVs from the same vehicle segment. This suggests that EVs and ICEVs have comparable usage in a multi-vehicle household.
- Household characteristics like size or having children have expected impact on vehicle preference: larger vehicles like vans and SUVs preferred, primarily ICEVs and PHEVs.
- College education, rooftop solar ownership, and number of employed workers in a household affect the preference of BEVs and PHEVs in the small car segment dominated by the Leaf, Bolt, Prius-Plug-in and the Volt often used as a commuter car.
- Among built environment factors, population density and walkability index of a neighborhood have a statistically significant impact on the type of vehicle choice and VMT. It is observed that a 10% increase in population density reduces the preference for ICEV pickup trucks by 0.34% and VMT by 0.4%. However, if the increase in population

density is 25%, the reduction in preference for pickup trucks is 8.4% and VMT is 8.6%. The other built environment factor we consider is the walkability index. If walkability index of a neighborhood increases by 25%, it reduces the preference for ICEV pickup trucks by 15% and their VMT by 16%. Overall, these results suggest that if policies encourage mixed development of neighborhoods and increase density, it can have an important impact on ownership and usage of gas guzzlers like the pickup trucks and help in the process of electrification of the transportation sector.

The model developed here using the 2019 California Vehicle Survey data suggests that though households may still have an inherent preference for ICEVs compared to BEVs and PHEVs in the vehicle segments where all three are available, when EVs are chosen they have a comparable usage. This result supports the need for incentive policies to encourage EV adoption and policies that encourage longer electric range EVs. Considering EVs entering the market continue to have improved electric range, one can expect EVs to increasingly have more comparable usage to ICEVs in a household. Further, the results related to household characteristics and built environment factors can inform California' state travel demand models and emission prediction models accounting for changes in vehicle preference and VMT as EVs penetrate the market. Moreover, the scenario analysis results here can be used to understand the impact of land-use and transportation policies on household vehicle holdings and usage that can in turn impact travel demand and air quality issues in the state.

Introduction

In the United States, in 2020, transportation sector was the highest emitter of greenhouse gas (GHG) emissions, accounting for over 27% of the total emissions, with light-duty passenger vehicles being a major contributor (57%)(*1*) . Light-duty vehicles also emit criteria pollutants which contribute to poor air quality. This has led policymakers both at the federal and state level to push for programs and regulations that encourage a transition from internal combustion engine vehicles (ICEVs) to battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), collectively referred to as plug-in electric vehicles (PEVs). California has a target of 5 million ZEVs (PEVs and Fuel Cell Electric Vehicles) on the road by 2030, and 100% of new vehicle sales being zero emission by 2035 (*2*). Based on the average carbon intensity of the California grid these 5 million PEVs are expected to release on average 20.8 million fewer metric tons (MMT) of well-to-wheel carbon dioxide equivalent (CO2e) than 5 million ICEVs (operating at an average of 24.3 miles per gallon [mpg]), which is 5% of total GHG emissions in California (*3*). These vehicle emission estimates are based on average driving behavior and average fuel efficiency estimates, not accounting for heterogeneity in travel behavior or the possibility of a rebound effect (i.e., increased driving due to decreased vehicle operating costs per mile). In practice, the emissions benefit of BEVs and PHEVs is related to how many gasoline miles are substituted by electric miles, where and when the PEVs are charged, and for PHEVs how many miles are driven using the electric motor vs. internal combustion engine.

In general, one may expect PEV adopters who trade off higher purchase prices for lower operating costs to maximize their electric miles. Critics have argued that in addition to replacing gasoline miles with electric miles, if lower operating costs however led to increased driving, i.e., the rebound effect, it would offset some or all the anticipated GHG emissions reductions. The severity of the concern is generally higher for PHEVs with a limited electric range and the capability of being driven as a gasoline vehicle. Multiple studies have focused on the topic of "rebound effect" for the conventional fuel vehicle market analyzing consumer sensitivity to operating costs and vehicle choice/use (*4–8*) . Along with operating costs, past studies on household vehicle usage of ICEVs, have analyzed the impact of built environment factors (*9*, *10*), and the inter-relationship between emission reduction policies, vehicle choice, and VMT(*11–14*).

The relationship between operating costs and vehicle usage and in general the potential for interactions between vehicle technology characteristics and VMT impacts are in general more complex for PEVs. Though there is a good understanding of the factors that encourage PEV adoption, the impact of the vehicle technology on VMT is far from clear. There are contradictions in the findings of past studies, depending on the type of PEV and the vehicle models studied. Analyzing the VMT of PEV owners from the 2017 National Household Travel Survey (NHTS), Davis (2019) finds that the average annual VMT of PEV owners is 30% lower than other fuel type vehicles. On the other hand, an analysis done by the Electric Vehicle Research Center for the California Air Resource Board show that PEVs are driven as much as gasoline cars not less (due to range anxiety) as some have suggested). Moreover, PEV VMT is found to be correlated with traditional factors like population density, built environment, attitudes towards technology, and lifestyle preferences. Specific to PEVs, electric driving range household electricity price, and access to infrastructure, have a major influence on PEV VMT. Based on the 2019 California Vehicle Survey data, similar factors were identified influencing VMT of PEVs in the study by Jia and Chen (*15*).Both these studies offer a simplistic analysis of PEV use either treating the VMT decision independent of the characteristics and usage of other vehicles in the household fleet or/and independent of the choice of the PEV itself. In either case, the endogeneity concern related to the link between VMT, and vehicle choice remains unaddressed.

Focusing on vehicle-owning households in California, using the 2019 California Vehicle Survey, this study analyzes the choice of vehicle technology and its usage in a joint model, namely the Multiple Discrete Continuous Extreme Value (MDCEV) choice model. The discrete component of the model allows us to estimate the choice of vehicle by body and powertrain type while the continuous part is to estimate the usage as a function of sociodemographic characteristics of the household and built environment characteristics of the household's residential zip code. The joint model of vehicle choice and VMT will give a more accurate measure of the effect of drivers of vehicle choice and use compared to the existing models focusing on the question of VMT of PEVs as it estimates the vehicle choice and usage behavior simultaneously within a utility framework. Nevertheless, this model does not consider the endogeneity concerns associated with the choice of home location/ density of the residential location and vehicle choice or usage (self-selection issue). While it is an important concern, past literature on this self-selection issues have not found any significant effects of residential self-selection once a rich set of covariates is controlled for(*16*). Moreover, in terms of choice of residential location and vehicle use, statistically significant but quantitatively small impact of residential density on household vehicle usage and fuel consumption(*17*, *18*).

Considering the GHG emission reduction targets and PEV adoption goals in California set by Senate Bill (SB) 32, ongoing policy efforts targeted towards auto manufacturers, and adoption trends, one can expect to see a rising share of PEVs in the vehicle fleet. Understanding the factors that influence driving behavior of PEV drivers will help to refine emissions impact assessment of these alternative fuel technology vehicles. A robust understanding of travel behavior of PEV drivers is also required to evaluate the efficiency and incidence of pricing mechanisms like the gas tax, mileage-based tax, or alternative mechanisms like a registration fee for PEVs. Finally, as the market for PEVs and PEV technology evolves, a better understanding of PEV VMT compared to ICEVs will become important for improving existing models for VMT analysis and forecasts like DynaSim, the California Statewide Travel Demand Model (CSTDM) or EMFAC used by California for travel demand and energy-use forecasting that are currently not well-developed to account for PEV penetration and potential changes in travel behavior.

The rest of the report is structured as follows. In Section 2 we briefly review the literature related to vehicle choice and VMT and the factors related to PEV usage. Next, in Section 3 we give a description of the survey data and the MDCEV model used to analyze the impact of the determining factors on the choice of vehicle and VMT. Findings from the econometric models are described in Section 4. Finally, we discuss the policy implications of the findings and the conclusions in Section 5 and Section 6 respectively.

Literature Review

Exploring factors that impact household and vehicle-level VMT has been a topic among researchers and policymakers for several decades, mainly due to the contribution of VMT to traffic congestion, emissions, and energy/fuel consumption. In the field of travel behavior, extensive research has been done on the impact of population density, built environment factors, land use characteristics, social network, spatial dependency, socio-demographics, and macroeconomic conditions on household and personal VMT (*19*–*22*). In addition, several studies have analyzed the impact of self-selection, namely the interaction between VMT and choice of residential location, neighborhood characteristics, or the type of vehicle (*10*, *23*, *24*). In a recent study, Singh et al. (*25*) analyzed the relative contribution of these factors on household VMT and found that socio-demographic variables explain 12% and self-selection effects account for 11% of the household VMT. They found 44% of the household VMT was unexplained and called for further research on the topic. Earlier analysis of residential location choice, primarily density and VMT have however found a statistically significant but small effect on VMT and consequent fuel consumption(*18*).

The economics literature investigates consumer response to changes in fuel costs or fuel economy improvements (the "rebound effect") in gasoline or hybrid vehicles. Controlling for macro-economic effects like employment rate along with most of the factors mentioned above, researchers have calculated fuel cost elasticity in terms of change in VMT at the regional-, household-, or vehicle-level (*5*, *26*–*29*). On average, the elasticity or "rebound effect" is estimated to be 8-14% with considerable heterogeneity by vehicle type, vehicle age, and household income (*7*). A few studies have differentiated the travel behavior of single- and multi-vehicle households and found that in the latter household type, the potential for "rebound effect" depends on the composition of the household fleet (*29*). In general, unlike single-vehicle households, a multi-vehicle household has the opportunity to respond to fuel prices by shifting miles to more fuel-efficient vehicles in their fleet and past research has found evidence of such behavioral response to an increase in gas price (*28*).

Fuel cost savings are generally a major motivation for the adoption of PEVs (*30*, *31*). Using interstate variation in gasoline and electricity rates, Sivak and Schoettle (*32*) observed that for all the states in the US the average annual fuel cost of driving a BEV with electricity efficiency of 33 kWh/100 miles is lower compared to an ICEV with an average fuel efficiency of 25 miles per gallon (*32*). Considering the motivation to purchase a PEV and the elasticity observed with fuel costs (*7*), one would expect that PEV owners would maximize the number of electric miles driven. However, there are contradictory findings in the literature in terms of PEV usage and VMT estimates. We could identify only a few studies that focus on PEV use and electric vehicle miles as a part of household travel demand. A recent study by Davis (*33*) using the 2017 NHTS data find that the average annual VMT of PEVs (descriptive analysis) is 30% lower than other fuel type vehicles (*33*). Burling et al. (*34*) also report that EVs are used less than expected based on the vehicle charging behavior of EV owners, raining questions about transportation electrification as a climate policy. On the other hand, analysis by Tal et al. (*35*) found that PEVs are being driven as much as gasoline cars, more so when travel behavior of long-range BEV owners is taken into account. Similar results were also reported by Chakraborty et al. considering households in California with a mix of gasoline vehicles and EVs in their household fleet (*3*). Nicholas and Tal (*36*) analyzed the factors that can influence the VMT of BEVs in a household and found that electric range, vehicle characteristics like body type, access to infrastructure, and vehicle sharing all play a role in how many miles a BEV has been driven annually (*36*). PEV adoption is often motivated by symbolic attributes like self- environmental identity, personal environmental and technology-related beliefs, or attitude towards risk. Hasan and Simsekoglu (*37*) addressed the effect of these psychological factors on post-purchase use of PEVs by single- and multi-vehicle households. The findings indicate that PEV use (i.e., annual mileage) is more sensitive to economic factors in single vehicle but more sensitive to perceived operating barriers in multi-vehicle households.

There are a limited number of studies on PEV use patterns due to a lack of reliable data on the travel behavior of PEV owners (*38*). Although the 2017 NHTS and 2019 CVS data offer researchers the opportunity to fill this gap in the literature it is essential to account for the characteristics of the sample of vehicles surveyed and the impact it may have on the VMT estimates. Early adopters of BEVs tend to have more vehicles in their household, are older, and more likely to be retired (*39*) all of which are correlated with lower VMT regardless of the vehicle technology owned. Further, the annual miles traveled estimate from the 2017 NHTS and the 2019 CVS publicly available data are based on single odometer readings (*35*). Using large-scale travel survey data such as the NHTS and the Residential Transportation Energy Consumption Survey (RTECS), past research has found that compared to dual readings, single reported odometer readings can be unreliable, especially when the survey respondent is not the primary driver of the vehicle (*6*, *40*). This study aims to address the limitations of prior PEV VMT studies by having a wider range of vehicle makes, models, and model years in the data sample, and by using odometer readings reported by households at two time-points to estimate VMT for PEVs. Compared to single odometer readings, dual odometer readings allow for more accurate VMT estimates as there are two data points to assess the validity of the self-reported odometer readings. Unlike existing PEV VMT studies investigating only the number of miles these vehicles are driven, we analyze overall household VMT in a single-vehicle PEV-only household and the distribution of VMT between PEVs and non-PEVs in a multi-vehicle household. The analysis in this study offers a better understanding of how PEVs are integrated into the household fleet and the factors influencing its usage in households with different numbers of vehicles.

Data and Methodology

Data

The analysis of vehicle choice and usage is done leveraging data from the California Vehicle Survey (CVS) administered by the California Energy Commission in 2019. As a result of the timing of the survey sampling and the survey itself, one may expect that the 2019 CVS data will capture the adoption and driving behavior of owners of second-generation EVs (longer vehicle range than the first-generation EVs) better compared to the 2017 National Household Travel Survey data, previously used to analyze the VMT of EV owners (*33*). The 2019 CVS surveyed total 4,248 households. Respondents are sampled randomly from the California population. However, FCEV owners are oversampled in the survey to get adequate representation of these vehicle owners in the survey. Since, the latter were not part of the random sample, we drop them from the data used for analysis. Considering the research question, we consider households with one or more vehicles in their household fleet. This implies we drop the 112 zero-vehicle households from the total sample.

Respondents report the annual mileage for each vehicle in their fleet. Since, the odometer readings and the mileage estimate are self-reported there are issues like recollection bias or simple misreporting of the reading (e.g., adding extra zeroes to the VMT estimate or dropping a digit). However, one of the distinctive features of the 2019 survey was the collection of dual odometer readings by the CEC for a subsample of the respondents. Ideally, dual odometer readings should allow for accurate estimates of annual VMT than a single odometer reading by raising the chances of detecting misreporting of odometer readings. But even the dual odometer readings collected for the 2019 CVS had challenges – insufficient real-time editing, data collection over different time frames ranging from a few days to a few years (for those using maintenance records), and misreporting. To improve the self-reported annual VMT estimates per vehicle of the household in the main survey, first, we separated the good and the erroneous dual odometer readings and used the former to clean the reported annual mileage data for each vehicle in a household. Note, the dual odometer readings were converted to annual VMT before they were used to correct the reported annual mileage data, but the widely differing measurement windows did introduce additional measurement errors. Second, the vehicles classified in the survey data as non-qualifying (for example, recreational vehicles) were removed from the dataset and the total number of household vehicles were then re-estimated for the households with non-qualifying vehicles. Third, to account for vehicles than are rarely driven in a household (e.g., vintage vehicles), we flagged vehicles with less than 10% of the total household VMT when the number of household vehicles is greater than number of drivers and vehicles less than 5% of the household VMT when number of vehicles is equal to the number of licensed drivers. We dropped the flagged vehicles from the analysis data and then re-estimated the total number of household vehicles. For vehicles with reported miles greater than 100,000 annual miles, we cap the annual mileage to 100,000.

The data on household demographic variables included in the analysis like household size, home tenure, rooftop solar ownership, or number of children are drawn from the California Vehicle Survey. Environment Protection Agency's (EPA) Smart Location Mapping Tool is used to control for built environment factors like population density and walkability index at the zip code level.

Methodology

While the interdependency between vehicle choice and miles traveled is well studied for gasoline vehicles with the help of multiple discrete continuous choice (MDCEV) models and its variants, joint multinomial discrete-continuous choice models, discrete continuous simultaneous equation systems, or the Bayesian Multivariate Ordered Probit and Tobit (BMOPT) model (*41–46*), studies focusing on VMT of PEV households have so far treated the choice of vehicle and VMT as independent decisions (*3*, *33*). But as in the case of gasoline vehicles, when households make choices and usage decisions involving PEVs, these will be affected by a wide variety of factors (e.g., vehicle characteristics, other household vehicles, fuel cost changes, socioeconomic characteristics, changes in commuting needs, or built environment factors) that cause these decisions to be interdependent. In fact, because of fundamental differences in the operating characteristics of EVs (electric range, recharging requirements), such interdependencies are even more likely for EVs than for conventional vehicles.

In this study, we estimate an integrated econometric model framework considering both discrete and continuous decision variables in the context of household vehicle ownership. A household may hold a mix of different vehicle types (e.g., sedans, vans, SUVs, or pickup trucks) or different vintages, and use the vehicles in different ways based on the preferences of individual members, considerations of maintenance and operating costs, and the need to satisfy various travel needs like commute trips, the ability to take long-distance trips, or transport goods. Past studies on vehicle choice and usage in an integrated framework mostly dealt with only ICEVs. In the past decade, since EV adoption has increased it is essential to consider fuel/powertrain type in the choice decision Here we take into account three main choices: vehicle body type, fuel/powertrain type, and annual mileage traveled. **Figure 1** gives the structure of the discrete-continuous model framework we estimate here.

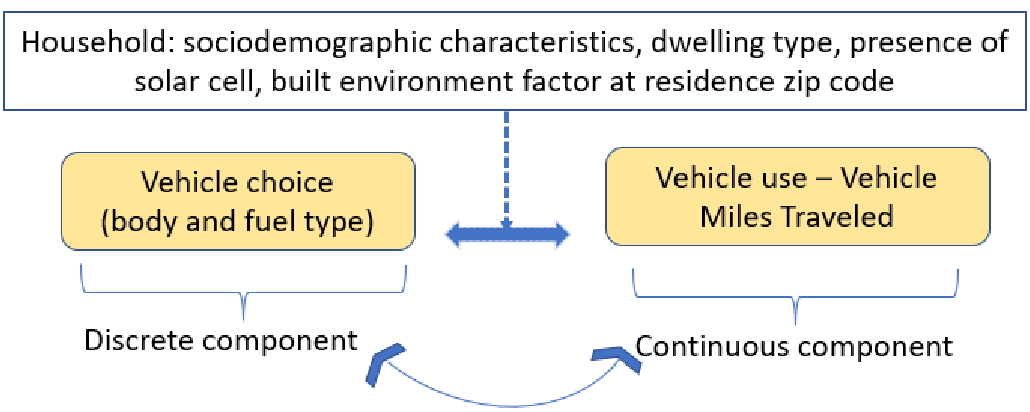

Figure 1. Structure of the integrated model

The integrated model framework we estimate here is the multiple discrete-continuous extreme vale (MDCEV) model that is based on the utility- maximization theory. The model handles multiple discrete choices using a generalized variant of the translated constant elasticity of substitution (CES) utility function with a multiplicative log-extreme value error term that makes the model analytically tractable and represent the multinomial logit form-equivalent for multiple discrete-continuous choice analysis. Considering the scope of research here, households maximize utility $U(x)$ associated with the consumption of different alternatives (here, vehicle types) subject to a binding linear budget constraint (here, it is total household

VMT). The utility function is a function of the alternative specific constants associated with a vehicle type, household characteristics, and other factors that may impact the choice of a vehicle type and its usage like built environment factors or attitudinal constructs. Applying the Kuhn-Tucker approach, the utility function is assumed to be random over the population, the randomness being incorporated through an error term in $U(x)$.

Let there be *K* different vehicle types (here, it is body type and fuel/powertrain type combination) that a household can potentially own and x_k be the annual mileage of use for vehicle type *k* (*k=1,2,3…, K*). The utility accrued to a household is the sum of utilities obtained from using each type of vehicle as expressed below:

$$U(x) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k} \psi_k \left\{ (\frac{x_k}{\gamma_k} + 1)^{\alpha_k} - 1 \right\}$$

Where, $\psi_k > 0 \; for \; all \; k$ represents baseline marginal utility of consumption of good k or the inherent preference for good k, higher value => higher preference for vehicle type *k*

$\gamma_k > 0 \; for \; all \; k$ determines the possibility of a corner solution, i.e., it is the translation parameter. It is also a satiation parameter, higher values => lower satiation effect in the consumption (miles driven) of vehicle type *k*.

$\alpha_k \leq 1 for \; all \; k$ represent the satiation effect associated with consumption of good k or the rate of diminishing marginal utility from using a particular vehicle type *k*. Higher the value of α_k lower is the marginal utility with increasing consumption of vehicle type *k*.

Here we estimate a MDCEV model assuming there is no outside good in the choice set of a household. In other words, corner solutions (zero consumption) are allowed for all the vehicle types. Moreover, both γ_k and α_k affect satiation and from the point of view of model identification it is very difficult to estimate both the parameters in one model and disentangle their effects. Here, we estimate a γ- profile model with a fixed value of $\alpha = 0 \; \forall \; k$.

The γ- profile model with no outside good collapses to a linear expenditure system as below:

$$U(x) = \sum_{k=1}^{K} \gamma_k \psi_k ln \left(\frac{x_k}{\gamma_k} + 1 \right)$$

To adopt a random utility specification for the model, the MDCEV framework applies the Kuhn Tucker condition. As a result, the baseline marginal utility becomes:

$$\psi(z_k, \varepsilon_k) = \exp(\beta' z_k + \varepsilon_k)$$

Where, ε_k captures the idiosyncratic or unobserved characteristics that impact the baseline utility for vehicle type *k*. z_k represents the set of vehicle-type constants, household characteristics, and built environment factors.

Therefore, the final MDCEV model set up with no outside good that we estimate here is:

$$Max\ U(x) = \sum_{k=1}^{K} \gamma_k [\exp(\beta' z_k + \varepsilon_k)] ln \left(\frac{x_k}{\gamma_k} + 1\right)$$

Sub to: $\sum_{k=1}^{K} p_k x_k = Total\ Household\ VMT,\ p_k = 1\ or\ unit\ price\ of\ k$

In addition to the MDCEV model, the authors also attempted the BMOPT model with the 2019 CVS data used here. The model is composed of a multivariate ordered probit model for the discrete choices and a multivariate Tobit model for the continuous choice. The joint model is formulated with an unrestricted covariance matrix for the discrete and continuous parts. It is able to handle a large number of vehicles and captures the interdependence (correlation) between the number of vehicles and total miles driven in each type of category, with flexible specification of error terms. However, considering the scope of the research here, the model set up required creating choice alternatives involving a combination of body and fuel type as done here. This created some categories with extremely low number of observations. Moreover, the computation became intensive for the large number of vehicle categories, as the number of equations to be estimated increased proportionally with the number of alternatives/vehicle categories. In other words, while it was possible to estimate the MDCEV model, there was identification challenges with the BMOPT model. Therefore, here we present results from the MDCEV model estimation.

Model Estimation Results

The MDCEV model accounts for the following choice decisions

1. Combination of body type of vehicle and Fuel/Powertrain type of vehicle
2. Number of miles traveled.

In terms of combination of vehicle body type and fuel/powertrain type we consider 18 categories: small-, mid-, large-car; sports car; small-, mid-, large-SUV; van; pickup truck in combination with ICEV, BEV, and PHEV powertrain-type. Gasoline, hybrid, diesel, flex-fuel, and CNG vehicles are combined under the ICEV category.

After cleaning of the household fleet-level data and augmentation with built environment data at the zip code level from EPA's Smart Location Database, 3,230 households remain in the analysis sample – 47% one-vehicle, 44% two-vehicles, and 9% three or more vehicles household. Table 1 lists the basic summary statistics of the vehicle body type-fuel type combinations in the household sample analyzed with MDCEV model.

Table 1. Summary statistics of vehicle body type- fuel type combinations

	Car				SUV			Van	Truck
	Small	**Mid**	**Large**	**Sports**	**Small**	**Mid**	**Large**		
Freq. ICEV	1,144	1,043	196	213	977	442	111	207	486
Freq. BEV	120	92	42		26				
Freq. PHEV	92	77	4		5			5	
Avg. VMT ICEV	10,056	10,204	9,454	6,289	10,579	9,985	10,651	9,394	9,659
Avg. VMT BEV	9,359	11,903	12,757		10,299				
Avg. VMT PHEV	12,753	12,018	20,432		12,075			11,267	

The baseline utility for each of the vehicle body-type and powertrain combinations is assumed to be a function of the following demographic variables: household income, household size, if the household have children less than 16 year old, if the household has 2 or more employed workers, highest education level in a household is college graduate or not, if a household has solar or not, and if it is a single-family home or not. In the model, household income is interacted with dummy variables for the powertrain categories to estimate the income elasticity or the relation between household income and the utility derived from ICEVs and EVs. The utility derived from a vehicle type can also depend on certain built environment characteristics of a household's neighborhood. In the model we include the following: population density, walkability index, job accessibility, public charger density, and if the household is in the San Francisco or Los Angeles County. Table 2 gives the basic summary statistics of the demographic variables included in the model and the definition of the built environment factors from the EPA Smart Mapping Tool.

Table 2. Summary statistics of the Demographic variables and Description of the Built environment Factors in the Model

Household Demographic Variables	Summary Statistics
Household Income (US dollar)	Average=$117, 345
Household Size	Average =2.1
Have children (less than 16 years)	17.8%
Two or more workers (full- or part-time)	27%
Highest education level in the household	79%
Have solar	15%
Single-family home	66%
Built Environment Factors	**Definition**
Population Density	Gross population density (people/acre) on unprotected land; averaged to zip code
Walkability Index	Based on measures of the built environment that affect the probability of whether people walk as a mode of transportation: street intersection density, proximity to transit stops, and diversity of land uses. (Scores 1-20; averaged to zip code)
Job accessibility	Jobs within 45 minutes auto travel time, time- decay (network travel time) weighted; aggregated to zip code
Public Charger Density	Total Level 2 and DCFC chargers/Total land area (acres); area aggregated to zip code
Residence Location (Los Angeles or San Francisco County)	LA: 43%; SF=23%

Results from the MDCEV model are reported in **Table 3** and **Table 4**. **Table 3** offers estimates for the baseline utility and the satiation parameters and **Table 4** gives the coefficient estimates for the explanatory variables included in the model like demographic characteristics and built environment factors.

Table 3. MDCEV Estimation Results - Baseline utility parameter and Translation/Satiation parameters

Parameter	Coefficient	t-ratio
Baseline Constants		
Small Car- ICEV (baseline)	0	
Small Car- BEV	-3.61	-6.11
Small Car- PHEV	-5.47	-7.36
Mid Car-ICEV	-0.14	-1.43
Mid Car-BEV	-3.78	-6.62
Mid Car-PHEV	-3.26	-5.23
Large Car - ICEV	-1.90	-9.98
Large Car - BEV	-6.02	-6.33
Large Car - PHEV	-8.14	-2.75
Sport Car- ICEV	-1.97	-11.51
Small SUV- ICEV	-0.21	-4.36
Small SUV - BEV	-4.93	-4.83
Small SUV- PHEV	-4.13	-2.39
Mid SUV - ICEV	-1.76	-11.13
Large SUV- ICEV	-3.94	-12.17
Van - ICEV	-3.12	-7.45
Van- PHEV	-11.35	-4.28
Pickup Truck- ICEV	0.03	0.14
Translation Parameters/Gamma	**Coefficient**	**t-ratio**
Small Car- ICEV	17.35	12.66
Small Car- BEV	16.11	5.06
Small Car- PHEV	31.71	3.49
Mid Car-ICEV	20.59	11.61
Mid Car-BEV	23.71	4.02
Mid Car-PHEV	26.50	3.55
Large Car - ICEV	18.23	5.56
Large Car - BEV	25.68	2.48
Large Car - PHEV	112.38	0.61
Sport Car- ICEV	6.88	7.52
Small SUV- ICEV	19.91	11.63
Small SUV - BEV	24.00	2.13
Small SUV- PHEV	36.73	0.73
Mid SUV - ICEV	16.35	9.05
Large SUV- ICEV	13.84	4.82
Van - ICEV	14.71	6.61
Van- PHEV	40.05	0.64
Pickup Truck- ICEV	10.21	10.51

Table 4. MDCEV Model Estimation Results: Explanatory Variables including Demographic characteristics and Built environment factors

Explanatory Variables	Estimate	t-ratio
Household Size		
Mid Car-ICEV	0.01	0.21
Large Car-ICEV	0.02	0.26
Van-ICEV	0.60	6.07
Van-PHEV	1.72	2.68
Mid SUV-ICEV	0.26	3.64
Large SUV-ICEV	0.64	4.93
Pickup Truck-ICEV	0.15	2.90
Have Children (At least one family member <16)		
Van- ICEV	0.07	0.31
Small SUV- ICEV	0.11	1.10
Mid SUV – ICEV	0.51	3.24
Large SUV- ICEV	-0.26	-0.95
College Education		
Small Car- BEV	0.90	2.17
Mid Car-BEV	0.34	0.89
Large Car - BEV	0.28	0.46
Small SUV- ICEV	-0.30	-1.27
Small Car- PHEV	1.16	2.29
Mid Car-PHEV	0.91	2.10
Large Car - PHEV	-1.14	-0.96
Small SUV- PHEV	0.96	2.32
Sport Car- ICEV	0.25	1.33
At least two Full-time/Part-time workers		
Small Car- BEV	0.38	1.98
Mid Car-BEV	0.26	1.20
Large Car - BEV	0.00	0.00
Small SUV- ICEV	0.10	0.25
Small Car- PHEV	0.41	1.90
Mid Car-PHEV	-0.41	-1.58
Large Car - PHEV	-0.74	-0.64
Household characteristics: Solar		
Small Car- BEV	0.91	4.51
Mid Car-BEV	0.92	3.87
Large Car - BEV	1.16	3.52
Small SUV - BEV	1.60	3.86
Household characteristics: Income Elasticity		
BEV	-0.25	-5.69
PHEV	-0.16	-4.91
ICEV	-0.04	-2.19

Explanatory Variables	Estimate	t-ratio
Household location: Los Angeles & San Francisco Region		
Small Car- BEV- LA	-0.41	-1.43
Mid Car-BEV - LA	-0.35	-1.03
Large Car - BEV - LA	0.70	1.46
Small SUV - BEV - LA	0.04	0.07
Small Car- PHEV- LA	0.79	2.52
Mid Car-PHEV- LA	0.08	0.24
Large Car - PHEV- LA	-0.73	-0.44
Small Car- BEV- SF	0.28	1.14
Mid Car-BEV - SF	0.49	1.70
Large Car - BEV - SF	0.84	1.81
Small SUV - BEV - SF	0.93	1.78
Small Car- PHEV - SF	0.45	1.38
Mid Car-PHEV- SF	0.59	1.91
Large Car - PHEV- SF	-0.33	-0.22
Small SUV- PHEV - SF	-0.51	-0.43
Built environment characteristics- Population density		
Small Car- BEV	0.02	1.81
Mid Car-BEV	0.01	1.26
Small Car- PHEV	0.00	-0.32
Mid Car-PHEV	-0.02	-0.77
Pickup Truck- ICEV	-0.04	-4.14
Built environment characteristics- Walkability Index		
Small Car- BEV	-0.56	-1.21
Mid Car-BEV	-0.04	-0.07
Large Car - BEV	0.73	1.02
Small SUV - BEV	0.31	0.35
Small Car- PHEV	1.14	1.98
Mid Car-PHEV	-0.28	-0.48
Large Car - PHEV	2.44	0.95
Small SUV- PHEV	-2.07	-1.08
Van - ICEV	-0.16	-0.59
Pickup Truck- ICEV	-0.70	-2.75
Built environment characteristics- Job Accessibility		
Small Car- BEV	0.18	1.43
Mid Car-BEV	0.24	1.77
Large Car - BEV	-0.10	-0.53
Small SUV - BEV	0.00	0.01
Small Car- PHEV	-0.16	-1.28
Mid Car-PHEV	0.11	0.69
Large Car - PHEV	0.42	0.77
Small SUV- PHEV	-0.69	-0.81

Estimates from the MDCEV model can be interpreted as follows:

Baseline constants ($\boldsymbol{\psi_k}$): represents the baseline utility associated with each of the vehicle body type-fuel type combination or the inherent preference for the alternatives. ICEVs have a greater baseline preference than BEVs and PHEVs for all body types. In case of mid-size car and small SUV though, PHEVs also tend to have a higher baseline preference than BEVs. In all other vehicle segments for which both BEVs and PHEVs are available, BEVs are preferred more than PHEVs. The negative sign on all the constants indicates a general baseline preference for small ICEV cars relative to all other vehicle body-fuel types.

Translation parameters ($\boldsymbol{\gamma_k}$): represent the satiation effect in a $\gamma - profile$ model. It captures how much households prefer to drive a particular vehicle body-type and fuel-type combination. EVs have a higher translation parameter than an ICEV for the body types in which all three exist. This shows that even though households may have a baseline preference for ICEVs, except in the small car segment, for all other body types, when households have both EVs and ICEVs, they tend to put more miles on the former. Sport cars have lowest value suggesting they are a specialized vehicle type and even though households may own these vehicles they tend to put less miles on these vehicles.

Household Characteristics: Larger households tend to have a higher baseline preference for Vans, SUVs, and pickup trucks, presumably because these vehicles are more spacious and comfortable for travel with bigger families. For potentially similar reasons, households with children (at least one adult le ss than 16-year-old) tend to prefer midsize SUVs. Households where at least one adult has a college degree, tend to have a strong baseline preference for BEVs and PHEVs in the small car, mid-size car and SUV segment. This follows the patterns reported in the EV adoption literature, high-level education positively correlated with EV adoption. Households with full-or part-time workers also show a preference for BEVs and PHEVs, potentially related to these vehicles being used for commute purposes that have shorter travel needs. Households with solar tend to prefer BEVs over small car ICEVs. However, there can be potential endogeneity issues associated with this variable; households with preference for BEVs due to unobserved attitudinal constructs or other unobserved sociodemographic factors may also prefer solar and vice-versa. Finally, BEVs are associated with highest income elasticity. BEVs are more expensive than other powertrains/fuel types in any vehicle segment (body-type) and as expected the preference for BEVs is higher when household income is high. None of the interactions with single-family home were statistically significant.

Built Environment Factors: Households with residence in LA county tend to prefer small car-PHEVs; potentially related to HOV lane use while households in SF county show preference for BEVs. The latter may be related to preference for technology in the SF area. Households in high population density areas tend to prefer small car BEVs but not pickup trucks; probably correlated with urban areas where there is lesser availability of parking locations and also the daily travel needs are more likely to be met by the range of currently available BEVs. Households in areas with higher walkability index do not prefer pickup trucks. Job accessibility has impact only on mid-car BEVs. Charger density has no statistically significant impact on BEV or PHEV preference.

The entire CVS sample is used for analysis here for in-sample estimation. The limited sample size does not allow splitting the data into a training and test sample that will allow a robust estimation of out-of-sample prediction accuracy. Moreover, the focus of analysis here is not on prediction, but explaining the factors associated with vehicle choice and usage in an integrated framework and illustrating how much EVs are used in comparison to ICEVs in the same vehicle segment.

Model Application – Scenario Analysis with Built Environment Characteristics

The MDCEV model estimated here can be used to determine the changes in vehicle type holdings and usage due to changes in independent variables over time. For example, past studies have shown that built environment factors like residential density or population density are associated with ownership of smaller vehicles and lower vehicle usage. Here we consider the impact of population density and walkability index on type of vehicle choice and VMT. The prediction method to assess the changes in vehicle ownership and use in response to changes in these built environment factors involve computing revised expected aggregate shares of different vehicle body-fuel type combinations and the total miles of usage of each combination, and then obtain a percentage change from the baseline estimates.

It is observed that a 10% increase in population density reduces the preference for ICEV pickup trucks by 0.34% and VMT by 0.4%. However, if the increase in population density is 25%, the reduction in preference for pickup trucks is 8.4% and VMT is 8.6%. The other built environment factor we consider is the walkability index. If walkability index of a neighborhood increases by 25%, it reduces the preference for ICEV pickup trucks by 15% and their VMT by 16%. Overall, these results suggest that if policies encourage mixed development of neighborhoods and increase density, it can have an important impact on ownership and usage of gas guzzlers like the pickup trucks and help in the process of electrification of the transportation sector. The results of the scenario analysis reinforce the findings of past studies that built environment factors like population density or infrastructure for non-motorized travel can encourage choice of fuel-efficient vehicles and reduce VMT. This has consequences both in terms of pollution reduction and the externalities associated with increased VMT.

Implication for State Travel Demand and Emission Prediction Models

In California, the state travel demand models like the California State Travel Demand Model (CSTDM) and the emission model like EMFAC were designed primarily to capture travel demand and emissions for a fleet dominated by ICEVs, primarily gasoline vehicles. For example, the CSTDM does not differentiate travel demand by type pf powertrain. As the adoption level of BEVs and PHEVs continue to rise driven by demand-side incentive policies or supply-side regulations to meet the electrification goals of California, it is important to account for BEVs and PHEVs in the fleet-mix- what are the factors that drive baseline preference for these powertrains and how much are they driven? It is observed that even if households may have a higher baseline preference for ICEVs, when they have a mix of EVs and ICEVs in their fleet, they tend to put comparable miles on the non-ICEV vehicle. This finding has consequences for both travel demand (in case there is a rebound effect due to lower operating costs of EVs) and emissions predicted by these state models.

Discussion

The results of the MDCEV model and scenario analysis indicate that the factors identified in prior literature affecting vehicle choice and usage patterns for ICEVs continue to be important in determining choice and VMT of EVs – household characteristics like size, education, income, or built environment factors like population density and the type of development (mixed or not). Additional household characteristics like ownership of roof top solar has an impact on EV ownership. In terms of vehicle usage, the results of the satiation factor show that the vehicle segments where all three powertrains are available, ICEVs, BEVs, and PHEVs, PEVs are used a comparable amount as ICEVs. The latter result is aligned with the findings of Tal et al. and Chakraborty et al.(*35*, *47*); both studies based on data from a cohort survey of owners of EVs of different generations and therefore different range. However, compared to the econometric models presented in these papers or those in the study by Davis, L. and Chen et al., the analysis here accounts for the potential endogeneity issue associated with vehicle choice and VMT (*15*, *33*). The analysis presented here is unweighted since the weights for the 2019 CVS data were not created as part of the survey data collection, but was a post survey analysis using the American Community Survey data.

The MDCEV model does not allow us to identify usage of individual vehicles at the household-level; the analysis focuses on the type/ category of vehicle as owned by households. As a result, it can be used to predict the VMT of different vehicle categories as identified in this analysis (body-type and fuel-type combination) but forecasting is out of scope of this project. Moreover, given the nature of the budget constraint in the current model set-up, the total household VMT, it is difficult to estimate the "rebound effect". Future model specifications, currently being developed by the team, will move away from using total household VMT as the budget constraint to an expenditure based MDCEV model. This will allow us to account for vehicle-specific attributes that may affect vehicle choice and usage as well as can potentially capture the impact of vehicle operating cost on VMT.

Conclusions

The increasing diversity of vehicle type holdings and growing demand for BEVs and PHEVs have serious policy implications for travel demand and air pollution. Consequently, it is important to accurately predict or estimate the preference for vehicle holdings of households as well as the vehicle miles traveled by vehicle body- and fuel-type to project future VMT changes and mobile source emission levels. The current report presents the application of a utility-based model for multiple discreteness that combines multiple vehicle types with usage in an integrated model, specifically the MDCEV model that answers the research question "what are the factors related to PEV choice and usage" while addressing the endogeneity concern. Important findings from the model include:

- Household characteristics like size or having children have expected impact on vehicle preference- larger vehicles preferred.
- College education, rooftop solar ownership, and number of employed workers in a household affect the preference of BEVs and PHEVs in the small car segment dominated by the Leaf, Bolt, Prius-Plug-in and the Volt often used as a commuter car.

Among built environment factors, population density and walkability index of a neighborhood have a statistically significant impact on the type of vehicle choice and VMT.

Considering vehicle choice and VMT in an integrated framework, the result of the analysis here suggests that along with some EV-specific factors like ownership of rooftop solar, usual factors that influence choice of ICEV vehicle types tend to impact the choice of PEVs as well in different vehicle segments- household and built environment characteristics. Moreover, the descriptive analysis of the 2019 CVS survey data show that compared to gasoline vehicles that are annually driven for 10, 057 miles, short-range BEVs are driven 9,122 miles and long-range ones are driven for 10,377 miles. The comparable usage of PEVs, including BEVs is supported by the satiation factors estimated by the MDCEV model here. Lastly, the joint modeling of vehicle choice and VMT here allows us to account for the fact that VMT estimation conditional on choice of a vehicle may also suffer from endogeneity concerns; households who drive more may be more gasoline price sensitive. As a result, they may also prefer BEVs and PHEVs that offer cost savings.

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Data Summary

Products of Research

No new data was collected for this research. We used publicly available data sources: the 2019 California Vehicle Survey administered by the California Energy Commission and Environmental Protection Agency's Smart Mapping Tool

Data Format and Content

The data was analyzed in R- Studio and it is in a CSV file, available on the Dryad data repository.

Data Access and Sharing

The data used for analysis is available on the Dryad data repository.

Reuse and Redistribution

The data used for analysis can be downloaded from Dryad and used for analysis by the public. There is no identifiable information in the CSV file. The data should be cited as follows:

> Chakraborty, Debapriya (2023). Role of vehicle technology on use: Joint analysis of the choice of plug-in electric vehicle ownership and miles traveled [Dataset]. Dryad. https://doi.org/10.25338/B8C64G