Household Demand for Clean Vehicles in California: Individual Attitudes, Current Car Ownership, and Future Car Ownership

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A Research Report from the Pacific Southwest Region University Transportation Center

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In this project an investigation of the key factors (such as attitudes towards electric vehicles, household characteristics, and past experiences) of vehicle purchase intention (future car ownership) by households is the core subject. Using observed data we determine whether eco-friendly vehicles (e.g., battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs)) have the potential in California based on *a three part analysis*. The data used here are the 2017 and 2019 California Energy Commission (CEC) vehicle surveys and the National Household Travel Surveys (NHTS). The objective of *the first part* is to explore behavioral attitudes, including both positive and negative attitudes toward battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). *The second part* explores if ZEVs lead to a higher number of Vehicle Miles Travelled (VMT) through an analysis of reported VMT of household fleet utilization in different years in the United States. *The third part* is a pilot study of willingness to pay for specific attributes of ZEVs mirroring an earlier research project on commercial fleets and now repeated for household fleets.

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About the Pacific Southwest Region University Transportation Center

The Pacific Southwest Region University Transportation Center (UTC) is the Region 9 University Transportation Center funded under the US Department of Transportation's University Transportation Centers Program. Established in 2016, the Pacific Southwest Region UTC (PSR) is led by the University of Southern California and includes seven partners: Long Beach State University; University of California, Davis; University of California, Irvine; University of California, Los Angeles; University of Hawaii; Northern Arizona University; Pima Community College.

The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education and technology transfer aimed at *improving the mobility of people and goods throughout the region.* Our program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) Improving resilience and protecting the environment; and 4) managing mobility in high growth areas.

U.S. Department of Transportation (USDOT) Disclaimer

Disclosure

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Abstract

In this project an investigation of the key factors (such as attitudes towards electric vehicles, household characteristics, and past experiences) of vehicle purchase intention (future car ownership) by household is the core subject. Using observed data we determine whether eco-friendly vehicles (e.g., battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs)) have the potential in California based on *a three part analysis*. The data used here are the 2017 and 2019 California Energy Commission (CEC) vehicle surveys and the National Household Travel Surveys (NHTS). The objective of *the first part* is to explore behavioral attitudes, including both positive and negative attitudes toward battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). *The second part* explores if ZEVs lead to a higher number of Vehicle Miles Travelled (VMT) through an analysis of reported VMT of household fleet utilization in different years in the United States. *The third part* is a pilot study of willingness to pay for specific attributes of ZEVs mirroring a previous research project on Commercial Fleets.

In the first part, clustering of respondents is first done based on vehicle attributes to group users' future vehicle intentions. Then a weighted multinomial logistic model (MNL) is developed to study the impact factors of people's future vehicle demand. Following that, three distinct models are evaluated to identify factors influencing consumer willingness to recommend three different zero-emission vehicles and potentially zero emission vehicles (ZEVs), namely plug-in hybrid electric vehicles (PHEVs), battery electric vehicles (BEVs), and hydrogen fuel cell electric vehicles (FCEVs), with past experiences (reflected by post-purchase satisfaction in this study) serving as mediators. Finally, the relationship between past experiences and future vehicle demand is discussed. Future vehicle choices are classified into four groups that based on fuel type, body size, vehicle addition or replacement, and desire for new or used automobiles. The results show that consumers who have experienced sustainable vehicles are more likely to continue to select them in the future. In terms of the impact factors of ZEV satisfaction and recommendation, PHEV owners are concerned about the costs associated with gasoline and electricity consumption at home. BEV users consider not just all of the aforementioned but also battery range and the availability of public charging stations. FCEV users value the convenience of refueling their vehicles. In the second part data from NHTS 2017 and 2022 are used to discern differences in annual reported VMT for vehicles of household fleets distinguishing between single vehicle fleets from multiple vehicle fleets and their correlation with vehicle types, fuel type, household composition and residential location. In the third part we explore the answers to hypothetical scenarios designed by a contractor for CEC, find significant factors of the propensity to use clean vehicles by households and then estimate their willingness to pay for specific vehicle attributes.

Household Demand for Clean Vehicles in California: Individual Attitudes, Current Car Ownership, and Future Car Ownership

Executive Summary

In this project an investigation of the key factors (such as attitudes towards electric vehicles, household characteristics, and past experiences) of vehicle purchase intention (future car ownership) by household is the core subject. Using observed data we determine whether eco-friendly vehicles (e.g., battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs)) have the potential in California based on *a three part analysis*. The data used here are the 2017 and 2019 California Energy Commission (CEC) vehicle surveys and the National Household Travel Surveys (NHTS). The objective of *the first part* is to explore behavioral attitudes, including both positive and negative attitudes toward battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). *The second part* explores if ZEVs lead to a higher number of Vehicle Miles Travelled (VMT) through an analysis of reported VMT of household fleet utilization in different years in the United States. *The third part* is a pilot study of willingness to pay for specific attributes of ZEVs mirroring a previous research project on Commercial Fleets.

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In the second part data from NHTS 2017 and 2022 are used to discern differences in annual reported VMT for vehicles of household fleets distinguishing between single vehicle fleets from multiple vehicle fleets and their correlation with vehicle types, fuel type, household composition and residential location. We find significant differences across the two cross sections of 2017 and 2022 and across household vehicle fleet sizes. Most important vehicles in multivehicle fleets are used by far less, fuel types play different in fleets of different sizes, and household structure is an important determinant of annual VMT. Moreover between 2017 and 2022 we see a variety of complex trends that support the need to continue tracking annual VMT in regular intervals and continue exploring its correlation with fueled used.

In the third part we explore the answers to hypothetical scenarios designed by a contractor for CEC, find significant factors of the propensity to use clean vehicles by households and then estimate their willingness to pay for specific vehicle attributes. The overall finding is that households appear to be willing to pay higher vehicle purchase price for attributes such as range and efficiency than the market offers.

1. Part 1 Household Car Ownership Analysis

In the context of global climate change, the adoption of sustainable transportation alternatives takes paramount importance as a means to decrease the release of greenhouse gases (Aminzadegan et al., 2022; Chen & Yang, 2022). In contrast to conventional internal combustion engine vehicles (ICEVs), sustainable vehicles like hydrogen fuel cell automobiles and electric vehicles (EVs) generate considerably lower emissions (Requia et al., 2018). In this situation, as a global leader in environmental policy and innovation, the California Air Resources Board initially implemented the Zero-Emission Vehicle (ZEV) requirement in 1990 as a component of the low-emission vehicle regulation (Collantes, 2006; Dixon et al., 2003). During the past three decades, the regulation has undergone modifications to align with the current advancement of technology. The ZEV requirements outlined in the Advanced Clean Cars II stipulate that all new vehicles in California must achieve 100% zero-emission and clean plug-in hybrid-electric by the 2035 model year (Ledna et al., 2022). In this report we label as ZEV all the vehicles that the California Air Resources Board lists as ZEVs and this includes plug-in hybrid electric vehicles (PHEVs), battery electric vehicles (BEVs), and hydrogen fuel cell electric vehicles (FCEVs). When needed we distinguished among the different technologies. With the automotive business moving to lower emission alternatives, investigating consumer vehicle preferences and behaviors becomes essential for manufacturers, policymakers, and other stakeholders (Lee et al., 2019).

Studying early adopters of lower emission automobiles has been a long-standing global topic (Haidar & Aguilar Rojas, 2022; Sharma et al., 2024). Prior research has examined several aspects of EV adoption, such as sociodemographic characteristics (Westin et al., 2018), psychographic variables (Okada et al., 2019), the availability of charging infrastructure (Charly et al., 2023), government policies (X. Zhang et al., 2014), different business models (Ziegler & Abdelkafi, 2022), and other related factors. In addition to adoption study, some scholars began analyzing users' satisfaction with EVs, which is of great significance as it can assist manufactures in keeping EV consumers (Kwon et al., 2020; Okada et al., 2019).

Despite the variety of research on the adoption and satisfaction of EVs, the majority of studies concentrate solely on the fuel type and disregard other vehicle attributes (Asadi et al., 2021; Yan et al., 2019), such as body size which may relate to comfort and functionality, vehicle addition or replacement, and preference for new or used vehicles. Those vehicle demand facets are critical for the manufacturing process and distribution of vehicles. To fill this gap, Goulias & Shi (2023) utilized principal component analysis to look into preferable attributes of vehicles (including fuel type, price, efficiency, size, timing of vehicle acquisition, addition or replacement, and intention of new, used, or leased vehicles). Nonetheless, that research is based on commercial fleets decision making, which could differ from households' decision making that is explored in this study.

Additionally, discussions on how past experiences with ZEVs influence future intentions have led to differing conclusions (Dua et al., 2024; Hardman & Tal, 2021; Jiang, 2023). It is crucial to determine whether ZEV users are likely to continue using clean vehicles or revert to traditional options such as internal combustion fossil fuel engine vehicles, as this would shape different strategies for improving the ZEV acceptance. If individuals are inclined to stick with ZEVs, efforts should focus on promoting adoption through incentives, awareness campaigns, and improved accessibility. Conversely, if people tend to discontinue using ZEVs, addressing their concerns by advancing technology, such as increasing driving range, extending battery life, reducing charging times, and enhancing overall performance and vehicle type variety, should become the priority.

Furthermore, there is absence of existing research in examination of individuals' propensity to recommend specific vehicle types to others. Yet, this is quite important as people's behaviors can be largely influenced by word of mouth (Bradford et al., 2017). According to Andrian (2022), a relationship exists between purchase intention and electronic word of mouth regarding low-cost green cars in Indonesia. Additionally, Ahn & Park (2024) emphasized that online review content has a substantial impact on the online purchasing behavior of consumers. In this context, the propensity of ZEV users to recommend them is also considered in this study, with post-purchase satisfaction serving as a mediating variable and examined as a strong determinant of endorsement.

This first part of the analysis in this project aims to answer following research questions:

(1) What are the characteristics of future vehicle intentions in terms of vehicle size, fuel types, adding or replacing vehicles, and new or used vehicles?

(2) How does people's past experience with ZEVs influence their own future vehicle intention?

(3) Which factors influence people's experience and satisfaction with ZEVs?

(4) Is there a relationship between people's satisfaction with ZEVs and their recommendation to other households?

To address the above questions, K-mode clustering is firstly used to investigate people's future vehicle choices in bundles of attributes, which reduces data dimension and simplifies our subsequent analysis and accounts for multiple attributes of an option jointly. Compared with other clustering techniques (such as principal component analysis), K-mode clustering is more resilient to outliers and easier to interpret while handling discrete and continuous data jointly (see details in Section 4.1). Second, a weighted multinomial logistic model (MNL) is developed to study the factors influencing people's future vehicle intentions. Following that, path analyses of three distinct models are performed to determine the underlying reasons for the willingness of consumers to endorse ZEVs (as mentioned this includes PHEVs, BEVs, and FCEVs), with past experiences (also known as post-purchase satisfaction in this study) serving as a mediator. Finally, the relationship between satisfaction levels and future vehicle inclinations is also examined here.

1.1 Brief Literature Review

Research on ZEVs covers a range of topics, including factors influencing adoption, societal impacts, and technological advancements (Asadi et al., 2021; Charly et al., 2023; Shi & Goulias, 2024; Yan et al., 2019). When it comes to studies on acceptance factors, many emphasize consumer concerns such as cost, awareness, and range anxiety (Okada et al., 2019). Demographic variables, including age, income, education, and whether individuals reside in urban or rural areas, are also analyzed to understand adoption patterns (Westin et al., 2018). External influences, such as government policies and market incentives, play a significant role in shaping ZEV adoption (Jenn et al., 2020). Subsidies and tax benefits have repeatedly shown their effectiveness in driving higher adoption rates (Cavallaro et al., 2018). Additionally, expanding reliable and accessible charging infrastructure remains essential to supporting and promoting ZEV adoption (Haidar & Aguilar Rojas, 2022).

To be specific, Zhang et al. (2014) examined the correlation between policies and the acceptance of EVs using the United States as a case study. Coffman et al. (2017) claimed that public charging infrastructure plays a significant role in facilitating the adoption of EVs, especially for BEVs, by alleviating range anxiety. Asadi et al. (2021) combined two commonly used theoretical models and found that personal values, attitudes, subjective norms, and personal norms are all influential elements that positively affect customers' decision to acquire EVs in Malaysia. Recently, Wong et al. (2023) discovered that EV adoption was encouraged by monetary incentives, free equipment, and guaranteed rides/batteries.

There are several methods for studying the acceptance of clean vehicles (Bhat et al., 2024; Kangur et al., 2017; Tiwari et al., 2020; Y. Zhang et al., 2017). Discrete choice models are commonly used to analyze consumer preferences and identify factors that influence purchase decisions (Bhat et al., 2024). Surveys and preference experiments can be conducted to directly collect consumer data. Structural equation modeling is useful for working with latent variables (unobservable factors like attitudes, perceptions, or satisfaction) that are measured indirectly through some observed indicators. Structural equations also help examine relationships among multiple independent and dependent variables, especially when mediators or moderators are involved (Tiwari et al., 2020; Werner & Schermelleh-Engel, 2009).

Simulation methods, such as agent-based models, are useful for modeling interactions among consumers, policymakers, and manufacturers (Kangur et al., 2017). Diffusion models, like the Bass Diffusion Model, are applied to study how innovations like ZEVs spread through a population (Bitencourt et al., 2021). Spatial econometric models can be used to explore regional differences in ZEV adoption and the impact of nearby infrastructure (Shi & Goulias, 2024). Time series models are able to analyze historical ZEV adoption data and predict future trends by considering seasonality, long-term patterns, and external factors (Y. Zhang et al., 2017).

Many studies have explored the adoption of ZEVs and its influencing factors using various models discussed above (Bitencourt et al., 2021; Coffman et al., 2017; Kangur et al., 2017). However, most of the studies focus solely on ZEV users while overlooking traditional vehicle owners. In this study, we include all vehicle users, both ZEV and non-ZEV owners, for comparison. A weighted MNL model is established to provide an unbiased evaluation. Additionally, existing studies often concentrate only on vehicle fuel types (Hardman & Tal, 2021; X. Zhang et al., 2014). One can enhance that by considering vehicles that use the same fuel type but differ in body size which affects comfort and functionality. which affects comfort and functionality. It is important to recognize that ZEVs are not limited to cars/ SUVs but also include electric pickup trucks. Moreover, understanding whether people prefer replacing their current vehicles with new or used ones is crucial for manufacturers' production direction. Therefore, it is essential to consider multiple vehicle attributes and subjective factors together for a comprehensive analysis as we explain next.

1.2 Data Used in the Part 1

The California Vehicle Survey (CVS) is regularly conducted to evaluate and update vehicle ownership data and estimate trends in vehicle usage. The California Energy Commission uses it as a data source to enhance the accuracy of its predictions regarding the energy needs of residential and commercial light-duty vehicles, as well as evolving preferences of market segments for any car ownership and use decision. The study in this paper focuses on the residential light-duty vehicle sector using the most recent CVS data from 2019. The data contain information on various sociodemographic factors, including gender, age, education, employment status, household structure, income, current vehicle ownership and usage behavior, and future purchase intention. Even though this study only focuses on California in 2019, the state serves as a strong example of the ZEV market dynamics (Ledna et al., 2022; Lee et al., 2019), providing insights applicable to other regions. Vehicle preferences elsewhere may follow similar trends, as many states now have ZEV adoption rates comparable to California’s in 2019. Europe also has a mature legislative framework with many similarities with California(European Commission, 2025). The findings in this paper are valuable for understanding broader adoption patterns and shaping policies in many established and emerging ZEV markets.

For the 2019 survey, the data collection consultant selected residential respondents from two sampling frames: (1) an address based sampling frame of households in California and (2) an online market research panel sampling frame of individuals in California. Finally, a total of 3,637 individuals completed the survey. However, a mere 8.52% of them had previous experiences with ZEV, which cannot contribute much to sustainable vehicle research. To counter this limitation, additional recruitment was carried out to focus on clean vehicle users to supplement the core samples. The targeted people were those who owned and operated at least one light-duty ZEV (PHEV / BEV / FCEV) registered for on-road operation in California. This provides an added 611 ZEV surveys. And our main analysis consists of 4,248 samples.

On one hand this provides enough samples of sustainable vehicles owners for in depth analysis. On the other hand, combining the ZEV added sample with the core sample presents biases. Table 1.1 demonstrate that there are variations in the sociodemographic characteristics of individuals between the core samples and ZEV samples. For example, middle-aged men were more likely to be in the ZEV samples, possibly due to their higher likelihood of having employment and earning a higher income. To mitigate the impact of sample biases on subsequent analyses, a weight is assigned to each ZEV sample according to the following formula (Stephen, 1981):

$$w_{ZEV} = \frac{n_t N_{ZEV}}{N_t n_{ZEV}} \tag{1.1}$$

Where n_t and n_{ZEV} is the total population and the population with ZEV experiences in ZEV samples, while N_t and N_{ZEV} is the total population and the population that had ZEV experiences in core samples. Since all respondents in ZEV samples were ZEV users, in our case, the weights of ZEV sample are actually the proportion of people with sustainable vehicle experiences in core samples.

Table 1.1 Descriptive statistics of sociodemographic variables for core samples and ZEV samples

Variables	Core samples	ZEV samples	Variables	Core samples	ZEV samples
Age groups			Household size	Min (1)	Min (1)
18To34	477 (13.12%)	51 (8.35%)		Mean (2.23)	Mean (2.65)
35 to 64	1,834 (50.43%)	412 (67.43%)		Median (2)	Median (2)
65 or over	1,326 (36.46%)	148 (24.22%)		Max (16)	Max (7)
Male	1,790 (49.22%)	452 (73.98%)	Household income		
Race			*Less then 10k*	58 (1.59%)	1 (0.16%)
Asian	483 (13.28%)	153 (25.04%)	*10k to 50k*	778 (21.39%)	32 (5.24%)
Black	155 (4.26%)	7 (1.15%)	*50k to 100k*	1,116 (30.68%)	97 (15.88%)
White	2,568 (70.61%)	360 (58.92%)	*100k to 200k*	993 (27.30%)	216 (35.35%)
Other	431 (11.85%)	91 (14.89%)	*200k more*	692 (19.03%)	265 (43.37%)
Education levels			Residential location		
Technical school or below	437 (12.02%)	34 (5.56%)	*Central Valley*	241 (6.63%)	8 (1.31%)
Some colleges	949 (26.09%)	82 (13.42%)	*Los Angeles*	1610 (44.27%)	312 (51.06%)
Colleges with 4 years	1,100 (30.24%)	190 (31.10%)	*San Francisco*	810 (22.27%)	195 (31.91%)
Post graduates	1,151 (31.65%)	305 (49.92%)	*Sacramento*	310 (8.52%)	33 (5.40%)
Full-time employment	1,465 (40.28%)	376 (61.54%)	*San Diego*	350 (9.62%)	38 (6.22%)

1.3 Methods

K-mode classification is a modified version of the commonly known K-means clustering algorithm. While K-means is designed for numerical data, K-mode is specifically suited for categorical data (Chaturvedi et al., 2001). The procedure entails initializing cluster centroids randomly by utilizing modes, which are the most frequent categories. It then proceeds to iteratively allocate data points to clusters based on their categorical similarity, as measured in Equation 2. The centroids are updated by reevaluating the modes within each cluster. This repeated assignment and update process continues until convergence.

$$d_c(X_i, C_j) = \sum \delta(x_{il}, c_{jl}) \quad (1.2)$$

Where $d_c(X_i, C_j)$ is the dissimilarity between the i_{th} observation and the j_{th} cluster, while l denotes the l_{th} variable. $\delta(x_{il}, c_{jl}) = 0$ for $x_{il} = c_{jl}$ and $\delta(x_{il}, c_{jl}) = 1$ for $x_{il} \neq c_{jl}$. Compared to some other clustering algorithms (e.g., principal component analysis), K-mode clustering is more robust to outliers. Since it uses modes (i.e., the most frequent values) to represent cluster centers, outliers have no substantial effect on the results. Furthermore, the clusters created by K-mode are more interpretable in terms of the categories they represent, which is useful for understanding patterns within the data.

This study utilizes eight categorical variables for K-mode clustering. These variables include three variables about vehicle fuel types that are conventional internal combustion engine vehicles (ICEVs), partial zero emission vehicles (PZEVs), and zero emitting vehicles (ZEVs). Another set of three variables are the body size (small, medium, and large) and a seventh variable indicating the addition or replacement of automobiles. The eighth variable represents people's preferences for new or used vehicles. More specifically, ICEVs include gasoline, diesel, and flex-fuel automobiles. PZEVs are gas hybrid vehicles. ZEVs consist of PHEVs, BEVs, and FCEVs. It is important to note that PHEVs differ from gasoline hybrid vehicles. PHEVs offer a significant all-electric driving range, enabling short commutes or trips without the use of gasoline. In contrast, gasoline hybrid vehicles rely on the electric motor primarily for supplemental power and efficiency, with limited capability to operate solely on electricity. In this case, we classify gasoline hybrid vehicles as PZEVs. Small autos include subcompact, small, midsize, large, and sports cars. The medium category contains subcompact crossovers, compact crossover/SUVs, midsize crossover/SUVs, and full-size/large SUVs. The larger vehicle type group involves small vans, full-size/large vans, small pickup trucks, and full-size/large pickup trucks.

There are, in general, several prevalent theoretical foundations that underpin purchase intention modeling: (1) According to the theory of reasoned action (TRA), an individual's conduct is impacted by their *subjective norms*, which denote the perceived social pressure from influential individuals to engage in or abstain from the behavior, and their *attitudes*, which pertain to their favorable or unfavorable perceptions of the behavior (Fishbein & Ajzen, 1975); (2) the theory of planned behavior (TPB) incorporates an additional determinant as an extension of the TRA (Ajzen, 1991; Yan et al., 2019), *perceived behavioral control*, which represents the perceived capability of the individual to execute the behavior; (3) the technology acceptance model (TAM), which proposes *perceived usefulness* and *perceived ease of use* as the foundational elements of information technology adoption, is another widely adopted model (Globisch et al., 2018; Venkatesh, 2000; Venkatesh & Davis, 2000); (4) the Unified Theory of Acceptance and Use of Technology (UTAUT) combines the essential elements of various behavioral models and proposes four primary factors that directly influence behavioral intention: *performance expectancy*, *effort expectancy*, *social influence*, and *facilitating conditions* (Venkatesh et al., 2003)."

In 2004, Schulte et al. stated that consumer purchasing behavior is influenced by *perceived risk*, which stands for the potential loss consumers associate with choosing a particular product, and *perceived return*, referring to the realistic benefits consumers expect to gain from adopting a product. In addition, *past experiences* (e.g., owning a car) can impact *perceived risk* and *perceived return*, ultimately influencing whether individuals choose to adopt a product or not. Moreover, prior studies have suggested that individuals' sociodemographic characteristics, such as age, gender, and educational attainment, may significantly impact their inclination to buy an automobile (Javid & Nejat, 2017; Vrkljan & Anaby, 2011). Considering the availability of relevant information in the 2019 CVS, this study incorporates four components into the future vehicle intention model based on the aforementioned theories, including *sociodemographic factors*, *facilitating conditions*, *residential locations*, and *past experiences* (see Figure 1.1). While the future vehicle intention can be measured in terms of fuel types, vehicle size, adding or replacing vehicles, and new or used vehicle purchase. *Attitudes* and *subjective norms* are considered in three ZEV distinct models (PHEV, BEV, and FCEV), despite the fact that they may not be referred to by the same name to maintain a straightforward expression (*sociodemographic factors*, *usage* of current vehicles, *refueling* and *parking* factors, and *financial* reasons) (Figure 1.2). For instance, we assume that individuals' perspectives on pertinent incentives can impact their perceptions of existing sustainable automobiles, thereby influencing their propensity to suggest others to use them.

Given that the result of the cluster analysis is a categorical variable, an MNL model was employed to investigate individuals' future vehicle intentions (Figure 1.1). This is similar to a commonly used discrete choice framework where individuals select one option from a finite set of alternatives (Hausman & McFadden, 1984; McFadden & Train, 2000). When the response variable Y has k unordered categories ($Y \in \{C_1, C_2, \ldots, C_k\}$), it can be modeled relative to a reference caregory (e.g., C_k):

$$\log\left(\frac{P(Y_i=C_m)}{P(Y_i=C_k)}\right) = \beta_{m0} + \beta_{m1}x_{i1} + \beta_{m2}x_{i2} + \cdots + \beta_{mp}x_{ip} \tag{1.3}$$

Where $P(\mathrm{Y_i} = C_\mathrm{m})$ and $P(\mathrm{Y_i} = C_k)$ represent the probabilities of the *i*-th observation being in categories $\mathrm{C_m}$ and $\mathrm{C_k}$, respectively ($\mathrm{m} \neq \mathrm{k}$). β denotes the coefficients, while *p* is the total number of explanatory variables. For observation i, the probability of being in category C_m is:

$$\mathrm{P(Y_i} = C_\mathrm{m}) = \frac{\exp(\beta_{\mathrm{m0}} + \sum_{\mathrm{j=1}}^{\mathrm{p}} \beta_{\mathrm{mj}} \mathrm{x_{ij}})}{1 + \sum_{\mathrm{r=1}}^{\mathrm{k-1}} \exp(\beta_{\mathrm{r0}} + \sum_{\mathrm{j=1}}^{\mathrm{p}} \beta_{\mathrm{rj}} \mathrm{x_{ij}})} \tag{1.4}$$

The probability of being in the reference category C_k is:

$$\mathrm{P(Y_i} = C_\mathrm{k}) = \frac{1}{1 + \sum_{\mathrm{r=1}}^{\mathrm{k-1}} \exp(\beta_{\mathrm{r0}} + \sum_{\mathrm{j=1}}^{\mathrm{p}} \beta_{\mathrm{rj}} \mathrm{x_{ij}})} \tag{1.5}$$

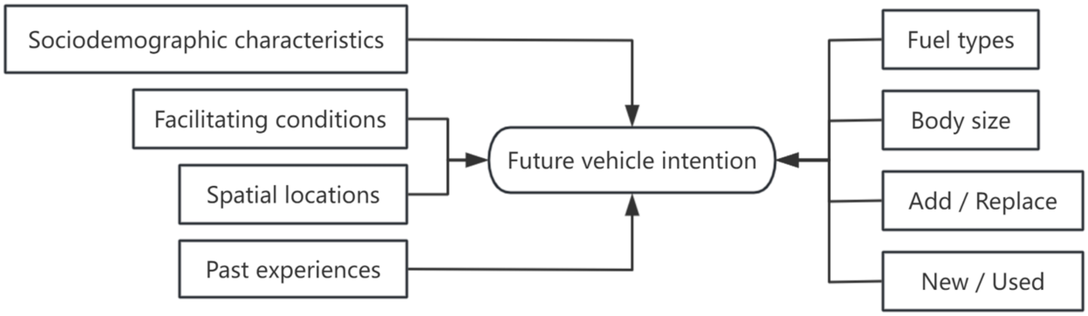

Figure 1.1 Model structures of future vehicle intention

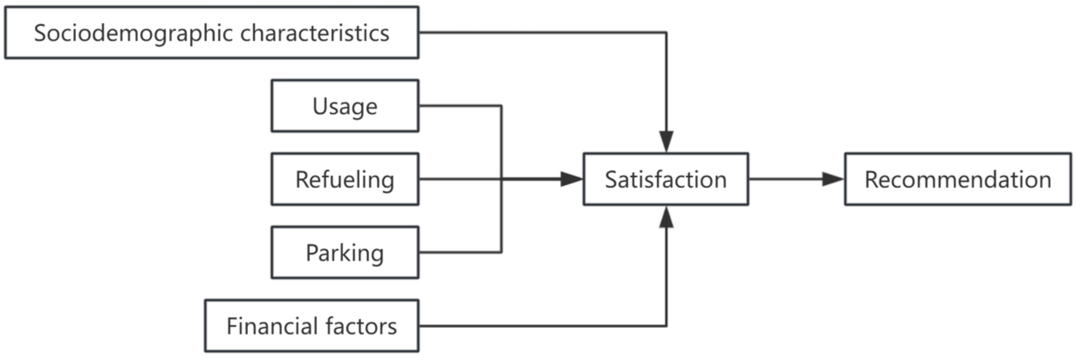

Figure 1.2 Model structures of ZEV recommendation

1.4 Results

To reduce the data dimension and simplify further analysis, the K-mode clustering method is employed to categorize individuals based on their intentions to acquire a vehicle of a fuel type, body size, adding or replacing vehicles, and whether they prefer new or used vehicles. The elbow approach based on minimizing the total sum of squares within clusters is utilized to ascertain the optimal number of clusters. Ultimately, the algorithm generates four clusters by simultaneously considering the total sum of squares within clusters and a minimum acceptable sample size in each group (all are over 10%). All variables have successfully passed the chi-square test (p-value < 0.1), indicating that each variable is significantly different from one another among the four groups. Table 1.2 shows the percentages of each category for each variable, whereas Table 1.3 lists the sample size of each cluster.

Overall, CVS members prefer to replace their existing vehicles with new small or medium-sized ICEVs or ZEVs. To mitigate the influence of these sample biases on the interpretation of cluster characteristics, we consider both the proportion of each category for each variable and the deviation of that proportion from the average proportion for the entire sample (as indicated in the last column of Table 1.2) in our subsequent analysis. Four clusters exhibit various inclinations toward their future automobiles. To be specific, the majority of people in the first cluster (980 persons; 23.07%) are interested in ICEVs (86.80%) in the future. Furthermore, they typically prefer medium-sized vehicles (68.70%). When compared the average proportions, the percentages for people preferring replacement and new vehicles are smaller (more than 2% difference). Therefore, this cluster is named *ICEV_NotSmall_MoreAdd_MoreUsed*. The second cluster consists of 836 individuals (19.68%), the majority of whom express interest in smaller, traditional or partly environmentally friendly vehicles (ICEVs/PZEVs) and this is dubbed the *ICEVorPZEV_NotLarge* group. The third cluster comprises 1,177 (27.71%) people, with the majority opting for ICEV or ZEV. They are less likely to be in the middle (in terms of fuel types) and do not prefer large automobiles. Furthermore, people in this cluster are more likely to replace existing cars with new ones than people in other groups and they are labeled *ICEVorZEV_NotLarge_MoreRep_MoreNew*. The final group is the largest, with 1,255 (29.54%) members. Most of them have a desire for small and most of them prefer sustainable vehicles (ZEVs) and therefore named the *ZEV_Small* group.

Table 1.2 Cluster characteristics of future vehicle intention based on category proportions of each variable

Variables	Categories	Clusters				**Total**
		1	2	3	4	
ICEV	Yes	86.80	81.00	75.00	24.20	63.90
	No	13.20	19.00	25.00	75.80	36.10
PZEV	Yes	14.20	77.80	35.30	23.20	35.20
	No	85.80	22.20	64.70	76.80	64.80
ZEV	Yes	22.70	40.40	85.60	86.50	62.50
	No	77.30	59.60	14.40	13.50	37.50
Small	Yes	20.00	84.00	78.00	87.00	68.50
	No	80.00	16.00	22.00	13.00	31.50
Medium	Yes	68.70	58.70	74.30	23.70	55.00
	No	31.30	41.30	25.70	76.30	45.00
Large	Yes	29.70	15.70	18.90	11.70	18.60
	No	70.30	84.30	81.10	88.30	81.40
Add or replace	Add	11.90	10.50	10.80	9.80	10.70
	Replace	77.20	80.90	82.10	78.80	79.80
	Other	10.80	8.60	7.10	11.40	9.50
New or other	New	61.00	64.40	66.70	64.00	64.10
	Other	39.00	35.60	33.30	36.00	35.90

Note: Each variable has its own color gradient. Light color (red/green) indicates low percentages, while dark color (red/green) represents high percentages.

Table 1.3 Labels and sample sizes of clusters

Clusters	Label	Number	Proportion
1	ICEV_NotSmall_MoreAdd_MoreUsed	980	23.07
2	ICEVorPZEV_NotLarge	836	19.68
3	ICEVorZEV_NotLarge_MoreRep_MoreNew	1,177	27.71
4	ZEV_Small	1,255	29.54
	Total	4,248	100.00

1.4.1 The weighted MNL of future vehicle intention

Based on the clustering results in an earlier section, a weighted MNL is carried out to investigate the effect of factors on future vehicle intention (see Table 1.4). As noted in Section 4.2, we consider people's personal and household characteristics, infrastructure, living environment, and previous experiences with sustainable cars (PZEVs and ZEVs). The *ICEV-NotSmall-MoreAdd-MoreUsed* cluster is designated as the reference group, as it enables us to directly focus on cleaner vehicles, such as ZEVs and PZEVs. This aligns with the primary objective of our study, which is to highlight the transition toward more environmentally friendly vehicle options. Only variables with statistically significant levels at 0.1 are kept in the model specification.

When considering sociodemographic characteristics, it is worth mentioning that young adults exhibit a higher propensity to experiment with electric automobiles. Men have a lower probability of being in the *ICEVorPZEV_NotLarge* category compared to the *ICEV-NotSmall-MoreAdd-MoreUsed* category, but white individuals show the opposite trend. It appears to be inconsistent with earlier findings that men are more likely to be in the ZEV samples, while those of white ethnicity are less likely to get involved in the ZEV group. Nevertheless, it is important to remember that the weighted MNL takes into account more factors, such as the size of the vehicles' bodies, as well as the replacement and acquisition of new ones. As expected, consumers with greater levels of education are more inclined to opt for sustainable automobiles, mostly because they possess a broader range of knowledge, covering environmental concerns and advancements in technology. Full-time employees prefer traditional or hybrid compact automobiles, probably because they are concerned about the battery life and replacement costs. Due to the high expenses associated with larger EVs, households are less motivated to pick sustainable vehicles as their household size increases. Furthermore, low-income families (earning less than $10,000 a year) do not exhibit any variations in their intention to purchase or lease a vehicle, most likely due to limitations in their financial situation. When their salaries reach a certain threshold, they are more likely to explore EVs, even more than wealthier families. This is possibly due to wealthier people focusing more on other attributes such as acceleration, brand prestige, and design styles. Regarding the past experiences of sustainable automobiles, it is important to note that earlier experience with EVs have a positive impact on users' future selection of electric version. This is mostly due to their possession of pertinent knowledge and heightened confidence in this still emerging technology. Moreover, a sufficient number of chargers could impact customers' choices of electrically powered vehicles. The residents of Los Angeles and San Francisco have a stronger preference for electric cars, mostly due to the impact of social norms but also higher presence of battery chargers.

Table 1.4 Parameter estimates of the weighted MNL of future vehicle intention

Variable	Clusters (Reference group: *ICEV-NotSmall-MoreAdd-MoreUsed*)		
	ICEVorPZEV_NotLarge	*ICEVorZEV_NotLarge_MoreRep_MoreNew*	*ZEV_Small*
Age Group (Base: 65 or over)			
18 to 34	0.35*	0.60***	0.19
35 to 64	-0.08	0.22*	-0.13
Male	-0.29***	-0.03	-0.11
White	0.24**	0.08	-0.02
Education level (Base: Technical school or below)			
Some Colleges	0.2	0.37**	0.04
Colleges with 4 years	0.65***	0.67***	0.46***
Post graduates	0.72***	0.93***	0.69***
Full-time	0.44***	0.12	-0.05
Household size	-0.13***	-0.09**	-0.13***
Annual household income (Base: Over $100k)			
Less than 10k	0.09	-0.35	-0.03
10k to 50k	0.2	-0.01	0.28**
50k to 100k	0.25**	0.06	0.13
Previous experiences with PZEVs	0.49**	-0.08	0.31
Previous experiences with ZEVs	0.04	0.79***	1.21***
See Chargers	0.44***	0.48***	0.36***
Residential location (Base: Rest of California)			
Los Angeles	0.30***	0.13	0.28***
San Francisco	0.58***	0.43***	0.79***
Constant	-1.73***	-1.62***	-1.00***
Observations: 4,248			
Accuracy: 0.36			
Likelihood-Ratio Test Statistic: 299.00***			

Note: *p<0.1; **p<0.05; ***p<0.01

1.4.2 Path analysis of ZEV recommendation

As stated in the introduction model establishment, social norms significantly influence the behavior of consumers. To enhance understanding of the prospective ZEV market, three path analyses are performed, employing satisfaction as the mediator, to ascertain the factors that most notably impact users' experience and consequently influence their recommendation to others (Figures 1.3 to 1.5). In general, statistical techniques can be applied to determine how well a hypothesized correlation pattern embedded in a statistical path model fits the observed data. Several statistical indices, such as Root Mean Square Error of Approximation (RMSEA), Tucker–Lewis Index (TLI), and Comparative Fit Index (CFI), are widely employed to assess the model fitness (Hu & Bentler, 1998). Table 1.5 summarizes the model fitness thresholds, with all three models meeting the criteria of good fitness. Only variables with 0.1 significant level are kept in models.

Given that some studies show ZEV owners may switch back to gasoline vehicles due to inadequate charging infrastructure, high costs, and challenges with long-distance travel (Dua et al., 2024; Hardman & Tal, 2021), our results across all three models indicate a strong positive correlation between owner satisfaction and their likelihood of recommending these vehicles to others. Additionally, some individual or household factors (such as age, level of education, and household size) no longer hold significant relevance in this context. This may be due to the fact that consumers of similar automobiles already possess certain demographic similarities to some degree.

To be specific, it seems that males hold more favorable views of PHEVs, but full-time employees do not share the same attitudes. This could be attributed to the shortage of charging infrastructure near their workplaces. Although PHEVs are equipped with internal combustion engines and do not strictly require charging, their primary advantage lies in their ability to travel significant distances on electric power, offering benefits such as lower fuel consumption, reduced emissions, and cost savings. Individuals who predominantly utilize gasoline rather than battery power are less inclined to have a positive experience due to lower savings from forfeiting the EV per mile cost reduction. It is also expected that they would have less confidence in their battery life. Furthermore, customers who value parking incentives are more likely to be happy with PHEVs. This suggests that California does indeed offer commendable parking incentives. As anticipated, if individuals suffer high costs for home charging, their satisfaction with PHEVs is likely to decrease. Regarding BEV owners, they are less likely to be Black or Asian from low-income families. Moreover, the greater the battery range, the more pleasant the experience. If users frequently charge their vehicles in public places, they likely hold negative attitudes toward BEVs. This finding could indicate that there is a shortage of public charging stations for EVs in California, likely resulting in lengthy waiting periods for charging. Finally, gasoline expenses are a crucial determinant. Like owners of BEVs, FCEV owners are more likely to be White. The rise in refueling frequency is indicative of the rising usage of FCEVs, which is accompanied by higher degrees of satisfaction. In addition, the convenience of refilling is also directly linked to usage satisfaction. Financial variables, such as the cost of gasoline, can exert an essential influence. Lastly, the more important consumers believe the manufacturer's or dealer's incentives are, the more likely they are to have positive experiences. This demonstrates that California does have suitable strategies in encouraging individuals to use sustainable automobiles.

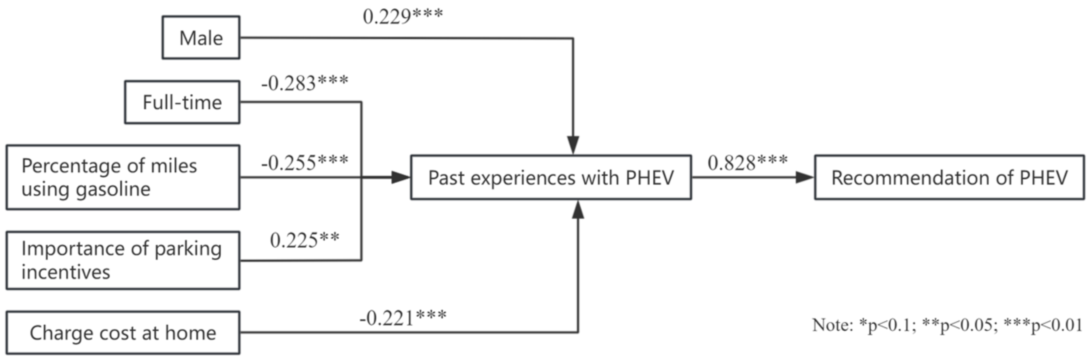

Figure 1.3 Path analysis results of PHEV recommendation

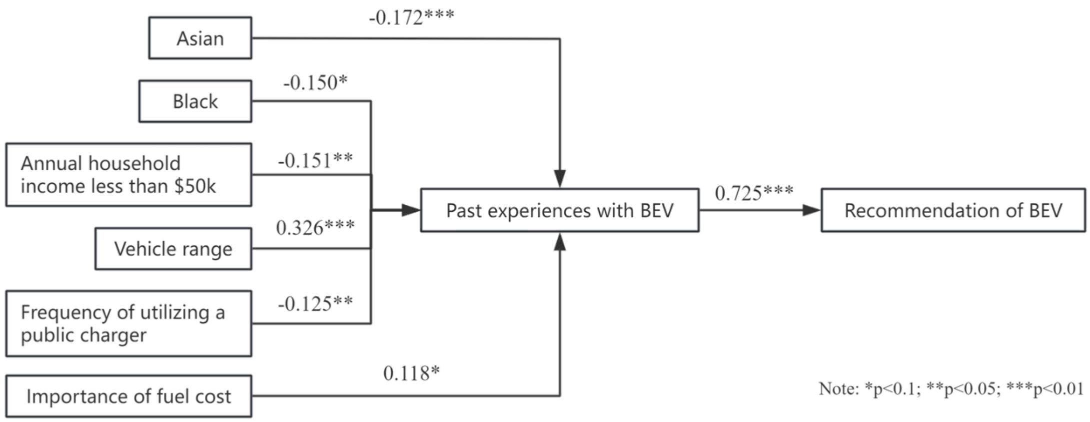

Figure 1.4 Path analysis results of BEV recommendation

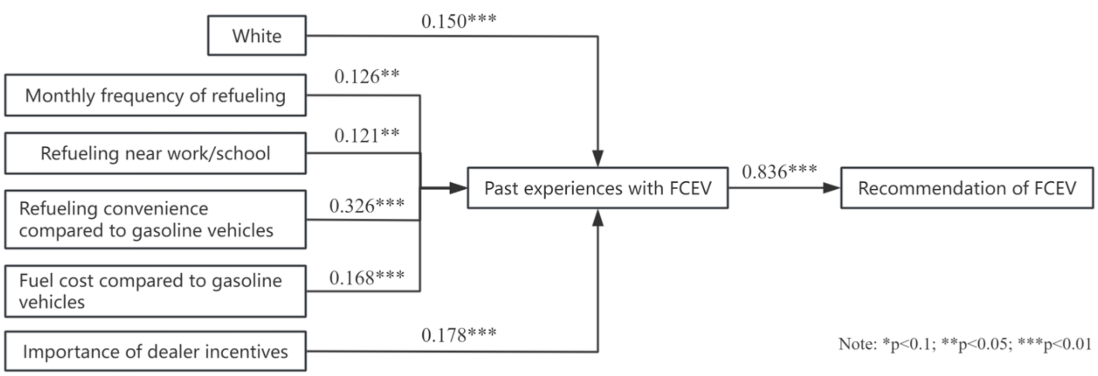

Figure 1.5 Path analysis results of FCEV recommendation

Table 1.5 Summary of the model fitness with thresholds

Models	Fit indices			Observation
	RMSEA	TLI	CFI	
PHEV model	0.064	0.973	0.988	173
BEV model	0.000	1.000	1.000	278
FCEV model	0.033	0.996	0.998	304
Thresholds	<0.10	>0.90	>0.90	-

Note: 0.000 and 1.000 are not exactly the same as 0 and 1. For example, the value could be 0.000001 or 0.999998.

1.4.3 Past experiences and future vehicle intention

Tables 1.6 to 1.8 summarize ZEV users' satisfaction with their existing vehicles and future purchase intentions for ZEVs. Overall, most car owners are content with their automobiles and want to select similar cars in the future. To be more exact, 78.03% of PHEV clients are considering purchasing another PHEV, while more than half (52.02% for BEV and 15.03% for FCEV) expect to try other EVs. This shows people gain familiarity with battery vehicles through PHEVs and become more confident about them. In this scenario, they are willing to try a similar type. Around 80% of BEV users intend to keep going with full-battery vehicles, while 44.42% are open to trying hybrid versions. This could be because some individuals encountered difficulties while charging their autos. In comparison, while more than half (60.20%) of FCEV users want to stay with their vehicle type, this percentage is substantially lower than for the other two groups. This is indicative of difficulty of hydrogen refueling, as mentioned in the previous section. In this situation, they express a relatively high desire to try PHEVs (49.34%) and BEVs (54.93%).

Table 1.6 Relationships between past experiences and future intention of PHEVs

Past experiences	PHEV User		Future intention		
	Count	Proportion	PHEV	BEV	FCEV
Unsatisfactory	3	**1.73**	0.58	1.16	0.58
Satisfactory	18	**10.40**	8.09	6.36	0.58
Excellent	43	**24.86**	22.54	12.14	3.47
Delightful	20	**11.56**	7.51	6.94	1.73
I love it	89	**51.45**	39.31	25.43	8.67
Total	*173*	*100.00*	*78.03*	*52.02*	*15.03*

Note: The value determines the color. Red denotes a large percentage, whereas blue signifies a low percentage.

Table 1.7 Relationships between past experiences and future intention of BEVs

Past experiences	BEV User		Future intention		
	Count	Proportion	PHEV	BEV	FCEV
I hate it	1	**0.36**	0.00	0.36	0.00
A failure	1	**0.36**	0.00	0.00	0.00
Unsatisfactory	4	**1.44**	1.44	1.08	0.72
Satisfactory	14	**5.04**	2.16	3.24	1.08
Excellent	40	**14.39**	8.27	10.43	2.16
Delightful	25	**8.99**	6.47	5.76	0.36
I love it	193	**69.42**	25.90	58.63	6.83
Total	*278*	*100.00*	*44.24*	*79.50*	*11.15*

Note: The value determines the color. Red denotes a large percentage, whereas blue signifies a low percentage.

Table 1.8 Relationships between past experiences and future intention of FCEVs

Past experiences	FCEV User		Future intention		
	Count	Proportion	PHEV	BEV	FCEV
I hate it	2	**0.66**	0.66	0.33	0.00
A failure	1	**0.33**	0.00	0.00	0.00
Unsatisfactory	15	**4.93**	2.63	2.63	0.33
Satisfactory	68	**22.37**	12.83	10.86	8.88
Excellent	69	**22.70**	10.53	13.16	13.82
Delightful	39	**12.83**	8.22	7.57	9.54
I love it	110	**36.18**	14.47	20.39	27.63
Total	*304*	*100.00*	*49.34*	*54.93*	*60.20*

Note: The value determines the color. Red denotes a large percentage, whereas blue signifies a low percentage.

1.5 Part 1 Analysis Conclusion

This study investigates whether or not users' future vehicle intentions are influenced by their prior interactions with sustainable vehicles, as well as whether or not these experiences impact their propensity to recommend such vehicles to other households. Specifically, K-mode clustering is first used to categorize individuals according to their vehicle preferences, including fuel type, body size, addition or replacement of vehicles, and preference for new or used vehicles. This enabled succinct subsequent analysis. Following this, a weighted MNL is computed to investigate the determinants of buyer's intentions. The results here demonstrate that past experiences do impact the future choices of individuals. In addition, path analyses of recommendation willingness are performed, with satisfaction levels of their existing ZEVs serving as mediators. Finally, an assessment is conducted into the correlation between present satisfaction levels with sustainable vehicles and future intentions.

Four distinct categories are identified with respect to car owners future vehicle preferences: (1) ICEV_NotSmall_MoreAdd_MoreUsed; (2) ICEVorPZEV_NotLarge; (3) ICEVorZEV_NotLarge_MoreRep_MoreNew; and (4) ZEV_Small. In general, Californians prefer to replace their existing vehicles with new small or medium-sized ICEVs or ZEVs. Additionally, individuals' sociodemographic status, living location, availability of refilling facilities, and previous knowledge all exert substantial influences on their vehicle preferences. PHEV owners are concerned about the costs associated with gasoline and electricity consumption at home. BEV owning people take into account not only the aforementioned factors but also the battery range and the availability of public charging. While FCEV users give high priority to the convenience of refilling their vehicles.

These findings suggest that there are several potential ways to increase ZEV markets and these include: (1) Governments can introduce targeted incentives to support vehicle charging at home, expand public charging infrastructure, and promote the installation of hydrogen refueling stations. In the context of home charging, advocating for the integration of home-based solar systems could further enhance sustainability and energy efficiency; (2) Manufacturers may seek incentives for offering enhanced battery quality. Hybrid small autos serve as a first stage in the transition from traditional vehicles to environmentally friendly vehicles. Moreover, it is important to note that sustainable large vehicles have a limited market share. This is predominately due to their prohibitively high prices. Governments and manufacturers could intensify collaborative efforts to expand the primary and secondary markets of large electric pickup trucks and/or vans as well as SUVs. Increasing driver exposure to the electric version may potentially foster a greater inclination towards its future usage, according to our findings of compact ZEVs. Following this course of action, more tax discounts and other advantageous policies could be implemented to promote the purchase of new electric large vehicles, such as incentives for charging and parking priority.

Also, governments should carefully evaluate the level of subsidies provided for ZEVs and determine an appropriate discount on electricity costs, which may inadvertently encourage individuals to drive alone. While ZEVs are environmentally friendly, excessive reliance on single-occupancy vehicles could exacerbate traffic congestion and lead to unnecessary energy consumption. In this context, identifying an optimal threshold for incentives becomes crucial to balancing the promotion of ZEV adoption with sustainable transportation practices.

Moreover, from an environmental standpoint, as highlighted by Cavallaro et al. (2018), BEVs typically generate fewer lifecycle carbon emissions compared to ICEVs. However, the extent of these environmental benefits largely depends on the carbon intensity of the electricity used for charging. In countries with low-carbon energy grids, such as Sweden, BEVs can achieve significant reductions in CO_2

emissions. In contrast, in regions where coal and/or petrol dominate electricity production, the emissions savings from BEVs are considerably lower. Consequently, a uniform subsidy policy is ineffective. Instead, financial policies should be designed to account for local energy contexts.

Unlike earlier research, this study focuses not only on vehicle fuel types, but also on other aspects suc as size, and transactions types that include fleet addition or replacement, and new versus used vehicle purchase. Moreover, the factors that influence satisfaction levels and recommendations are explored. Our findings here serve as guidelines: (1) clarifying to manufacturers specific facets of automobiles they should prioritize in production and identifying their intended market base; (2) assisting the government in continuously maintaining and/or increasing the number of policy diversity targeting the needs of specific segments interested in environmentally friendly vehicles.

Given the advantages mentioned above, our analysis is based on data from California collected before the COVID-19 pandemic in 2019. Existing research suggest that ZEV adoption patterns may have shifted in recent years and that ZEV sales could vary significantly across regions (Shi & Goulias, 2024; Wong et al., 2023). In the future, as new data from various regions and countries becomes available, further investigations can explore whether individuals have changed their vehicle preferences over the past five years across different locations. Notably, the California Energy Commission is currently testing a new survey. This future analysis can also be linked to regional energy usage and emissions to provide more detailed suggestions for achieving sustainability. In addition, some studies have highlighted that financial and geographic barriers can limit access to ZEVs for disadvantaged groups (Canepa et al., 2019). Future research should focus on these vulnerable communities to promote equitable access and support sustainable mobility.

2. Part 2 Annual Vehicle Miles Travelled

Car ownership and the impact of motorization is a long-standing research topic in travel behavior and motivated a variety of studies spanning a wide spectrum of policy questions from social exclusion (Lucas, 2012), cultural and social assimilation (Beckman and Goulias, 2008), beliefs and attitudes towards sustainability (Steg, 2007), residential location choice and car use (Lee and Goulias, 2018), urban development/land use (Giuliano and Dargay, 2006) and of course the strong relationship with fuel type choice (Van Wissen and Golob, 1992). A comprehensive review by Jong et al. (2004), Potoglou and Susilio (2008), of early car ownership models and a more recent UK focused review by Bhagat et al. (2024), identify many determinants of the decision to own vehicles and the formation of vehicle fleets. Steg (2007) provides an overview of the push and pool policies to decrease car use and hints on the possible heterogeneous motivations of people in favor or against car ownership and use. This theme is explored by developing seven latent car ownership segments accounting for attitudes with attention paid to the vehicle types and heavily individual oriented analyses Wang et al., 2022). As shown elsewhere, however, car ownership by type and use of cars in a household is a very complex dynamic phenomenon that requires longitudinal records or retrospective records of transactions and diaries of car use to untangle the influence of many different factors (Rashidi et al., 2011, Khan and Habib, 2021,). When we consider zero emissions or close to zero emission vehicles, the use of these vehicles because of their lower per mile cost of using them adds to this complexity possible rebound impacts Chakraborty et al., 2022). In addition, infrastructure development and spatiotemporal market evolution has a significant impact on car ownership and possibly and use (Shi and Goulias, 2024). In essence this is the claim that lower everyday costs of running an electric car may motivate people to drive that car more and accumulate more vehicle miles travelled and contribute to congestion.

In this report we explore a few correlations that other researchers found between car types and car use by households exploring the data provided by the National Household Travel Surveys (NHTS) of 2017 and 2022. We show that Annual Vehicle Miles travelled require special attention in the way data are analyzed, and household fleets need to be differentiated between one car owned versus two or more cars owned by a household. We also show that individual based analyses may suffer from biased regression coefficients and therefore any conclusion about demand elasticity to internal to the household and external to a household factors should be considered with extreme caution.

2.1 Data Used in the Second Analysis

NHTS in 2017 and 2022 provide a vehicle file that contains information about each vehicle owned by each household taking part in the survey. Fuel type in these two cross sections is reported for each vehicle in categories that are different between the two NHTS years. The sample sizes are also very different with NHTS 2017 providing data for many more households that NHTS 2022 (McGuckin, N., & Fucci, A. ,2018, Bricka et al., 2024).

For 2017 and 2022 NHTS provides sample weights to create estimates standing for the entire civilian US population (Westat, 2019, Ipsos, 2022). These are in essence expansion weights. In this report we focus on the Table 2.1 shows the survey number of household vehicles by fuel type with a clear trend doubling of the percentage of hybrid, plugin, and all electric vehicles between 2017 and 2022. Diesel vehicles show a small decrease from 2017 to 2022 in percentage of market penetration. There is also a notable increase in other fuels such as biodiesel. These are millions of vehicles in the US showing a substantial market size and trend. Gasoline vehicles on the other hand show a decrease in market share but still showing more than 92% of the market that is in the hundreds of millions dominating all other fuels. It is possible, although not directly nationwide testable, that during those years a spatial dispersion of the alternatively fueled vehicle market is happening mimicking the events in California documented in Shi and Goulias (2024). The large difference in sample sizes between 2017 and 2022 motivate us to do two parallel analyses to avoid 2017 overwhelming the analysis of 2022.

Table 2.1 NHTS Survey Vehicles by Type of Fuel with Weighted Population Estimates

Year	2017				2022			
Code in Databases	Number of Vehicles	Percentage	Weighted Number of Vehicles	Percentage	Number of Vehicles	Percentage	Weighted Number of Vehicles	Percentage
Codes -7, -8, -9 = unknown	325	0.13%	337593	0.15%	32	0.22%	475793	0.20%
01=Gas	241759	94.39%	211899839	95.20%	13485	91.83%	214859181	92.28%
02=Diesel	7422	2.90%	5441249	2.44%	384	2.62%	5494116	2.36%
03=Hybrid, plugin, or electric*	6416	2.51%	4766108	2.14%	743	5.06%	11113234	4.77%
97=Some other fuel	193	0.08%	134158	0.06%	40	0.27%	894780	0.38%
Total	256115	100.00%	222578947	100.00%	14684	100.00%	232837104	100.00%

Notes: *In 2022 NHTS reported separately Hybrid, Plug-in Electric and Electric vehicles. In the analysis here we do the same whenever possible.

2.2 Vehicle Miles of Travel

The introductory paragraph of a paper on the use of Vehicle Miles of Travel (VMT) as a key performance indicator of planning is indicative of the hope bestowed to VMT reduction (Salon et al., 2012) who write: "Reducing vehicle miles traveled (VMT) would generate many benefits. These include alleviating traffic congestion, reducing air pollution, reducing greenhouse gas emissions, reducing our dependence on foreign oil, improving public health through increased exercise, and enhancing interactions within our communities. A number of state governments – including California, Washington, and Florida – have recently passed legislation aiming to rein in VMT, and many cities have independently begun to reduce VMT in their jurisdictions."

In the past ten years, however, market penetration of lower emission and also zero emission vehicles and their substantially different operating characteristics may change the correlation between VMT and emissions if the zero emitting vehicles substitute the internal combustion engine (ICE) fossil fuel vehicles and if they are used in a similar way as ICE vehicles. The data in NHTS 2017 and 2022 offer a unique opportunity to explore the relationships among VMT accumulated by different fueled vehicles and to also account for the role played by fleet size and composition in households.

Household ownership is a decision treated as a series of nested decisions at the household level (Ben-Akiva and Lerman, 1975, Bhat and Pulugurta, 1998, Nolan, 2010, Oakil et al., 2014, Goulias, 2018, Haque et al., 2019). The number of vehicles and the typer of vehicles in the household fleet affects travel behavior in nonlinear ways as households climb at higher levels of ownership (Kitamura and Kostyniuk, 1986). We also see asymmetries when households dispose of vehicles (Pendyala et al., 1995), and strong correlation with the built environment (Sabouri et al., 2021, Laviolette et al. 2022). However, all these determinants and their impact on car ownership, car type, fuel type, and use of vehicles is even more complex when we consider values, norms, attitudes, and constraints of observed behavior (Goulias, 2024) and the first part of this project report.

Self-selection bias and strong unobserved correlation among residential location, work location, car ownership, and daily travel behavior require untangling of observed and unobserved correlations using more complex models than customary utility-based choice models (see the series of papers by Silva et al. 2006, Silva et al., 2009, Silva et al., 2012a, Silva et al., 2012b, Silva, 2014). This untangling is even more complex when we consider individual and household experience with specific vehicle technologies (Shi and Goulias, 2024) and when we explore technologies that are only now becoming visible on-the-road (Xiao and Goulias, 2022).

In this project we develop a simplified analysis that pays attention of an often-neglected aspect in car ownership, vehicle and fuel type, and VMT. In the literature we find travel behavior indicators are influenced in different ways depending on the level of cars per household member and/or household driver. We also know that vehicle allocation to household members depends on household roles and responsibilities (Petersen and Vovsha, 2006, Vovsha and Petersen, 2007, Habib, 2014). When analyzing VMT per vehicle and we aim at identifying significant correlation with vehicle fuel (e.g., are gasoline vehicles used less than electric cars?), with vehicle size and type (e.g., are passenger cars used more often than SUVs?), household composition (e.g., do children motivate their parents to accumulate more VMT?), or the impact of the built environment and region on VMT (e.g., are vehicles operated in large metropolises of California displaying higher VMT?). Estimation of these correlations of vehicles that belong in the same household fleet are biased (and the elasticities thus derived wrong) if an explicit accounting of the within household fleet correlation is neglected. One way to account for this correlation is to use multilevel regression models and cluster analysis (Goulias, 2002, Lee at al., 2016). The multilevel methods have been tested on a variety of travel behavior indicators as well as cross-sectional and longitudinal data (Goulias, 1999, Goulias and Kim, 2001, Viswanathan and Goulias, 2001, Goulias, 2002, Chung et al., 2004, Kim and Goulias, 2006, Kim and Wang, 2015, Lee and Goulias, 2018, Zhang et al., 2021, Buelher et al., 2024)

The model specification presented in this report follow examples from the literature on assessing the substantive impact of VMT correlations with vehicle attributes, personal characteristics, household composition and structure, and geographic location (e.g., Wang and Chen, 2014, Singh et al., 2018). We also expect to find different classes of vehicle use as in Nazari and Mohammadian, 2023. We also know that there is substantial measurement error in NHTS reported VMT per year (Alberini et al., 2021) and we devised a method to alleviate this in the regression models as explained later. Below we provide the reasoning behind the model specification of VMT developed here using groups of explanatory factors for the regression models. In specifying the VMT regression models that follow we considered a variety of known influencing factors found in our own research and the literature shown below.

Vehicle Attributes and Purposes

It is widely recognized that vehicle attributes, including size, age, and fuel type, along with usage purposes, significantly influence individuals' travel behavior (Barnes & Langworthy, 2004; Chonhenchob et al., 2012). Specifically, larger vehicles, such as vans and trucks, are often associated with commercial use and higher annual mileage. Older vehicles tend to be less reliable and fuel-efficient, prompting owners to avoid long-distance or non-essential travel. Additionally, fuel type can also shape travel behaviors. For example, Zhang et al. (2018) pointed out that private autonomous vehicles (AVs) can reduce vehicle ownership but may significantly increase household vehicle miles traveled (VMT) generation. Furthermore, vehicles used for commercial purposes, such as delivery services or ride-sharing platforms like Uber/Lyft, typically accumulate higher annual mileage compared to personal use vehicles. According to Henao and Marshall (2019) study, ride-hailing increases VMT by approximately 83.5% compared to a scenario without it.

Psychological Foundations

As mentioned earlier the *Theory of Reasoned Action* (TRA), developed by Fishbein and Ajzen (1975), explains human behavior as a result of intentions, which are shaped by attitudes (positive or negative evaluations of behavior) and subjective norms (perceived social pressure). Recognizing the limitations of the TRA in situations where behavior is not entirely under volitional control, Ajzen (1985) introduced the *Theory of Planned Behavior* (TPB), adding perceived behavioral control (the individual's belief in their ability to perform the behavior) as a third factor. This extension made the TPB more applicable to real-world scenarios where external or internal barriers influence behavior. Later, Aarts et al. (1997) introduced *Habitual Travel Behavior*, emphasizing how individuals rely on ingrained routines, making behavioral change difficult. Nowadays, with the growing impact of climate change, environmental considerations have become an important factor in people's travel decisions. For example, Dimitropoulos (2014) concluded that individuals with environmental concerns tend to prefer plug-in electric vehicles.

Sociodemographic Influences

Furthermore and as expected, travel behavior is also influenced by sociodemographic factors, as highlighted by Jones et al. (1983), who introduced the *life-course approach*. It shows how travel demand fluctuates across life stages. Expanding on this, Clark et al. (2014) demonstrated that major life events, such as job relocation, marriage, the birth of children, and retirement, significantly influence long-term travel behavior. In addition to the factors mentioned above, fundamental indicators such as gender, race, household income, and the number of vehicles also play a significant role (Vrkljan & Anaby, 2011).

Land Use and Spatial Impacts

In 1970, Hägerstrand introduced *Time-Space Geography*, showing how mobility is constrained by time and spatial limitations. Cervero and Seskin (1995) provided a thorough review of key studies from the past three decades on the relationship between transit and urban form. Badoe and Miller (2000) examined empirical research on the *land use and transportation interaction* and found that factors such as urban densities, traditional neighborhood designs, and land-use mix could influence auto ownership and use. After that, Duranton and Turner (2011) validated the concept of *induced demand*, showing that expanding roadways or public transit is unlikely to reduce congestion.

Policy and Financial Factors

Policy and financial mechanisms could also play a critical role in shaping travel behavior. Calthorpe (1993) introduced *Transit-Oriented Development* (TOD), emphasizing the role of policy in promoting compact, mixed-use developments near transit hubs to reduce car dependency. Shoup (1997) demonstrated that abundant free parking promotes car use, and advocated for market-based parking pricing to reduce car dependency. Gärling and Schuitema (2007) concluded that coercive *Travel Demand Management(TDM)* measures can be more effective and widely accepted when paired with strategies that offer appealing travel alternatives and highlight the benefits of reducing car use. In addition, Ettema et al. (2010) suggested that positive incentives can reduce participants' peak-hour traffic by approximately 60%. Wang and Chen (2014) showed the potential of using fuel prices as a tool to influence VMT.

Based on the above discussions and considering the data availability of the NHTS dataset, we have developed a conceptual framework for exploring the determinants of annual vehicle miles traveled and the VMT regression model specification. Figure 2.1 provides a summary of the relationships we expect to find as significant explanatory variables in model of Annual VMT for each vehicle in the NHTS data. Table 2.2 shows an example of the data in NHTS using the multivehicle fleet data of 2022 NHTS. The sections that follow are divided into the analysis of vehicles that are in household fleet with one vehicle only and analysis of vehicles in household fleets with more than one vehicle that as explained earlier requires a multilevel regression analysis. The analysis is repeated for NHTS 2017 and 2022 separately because the sample size of NHTS 2017 is by far larger than the sample size of NHTS 2022.

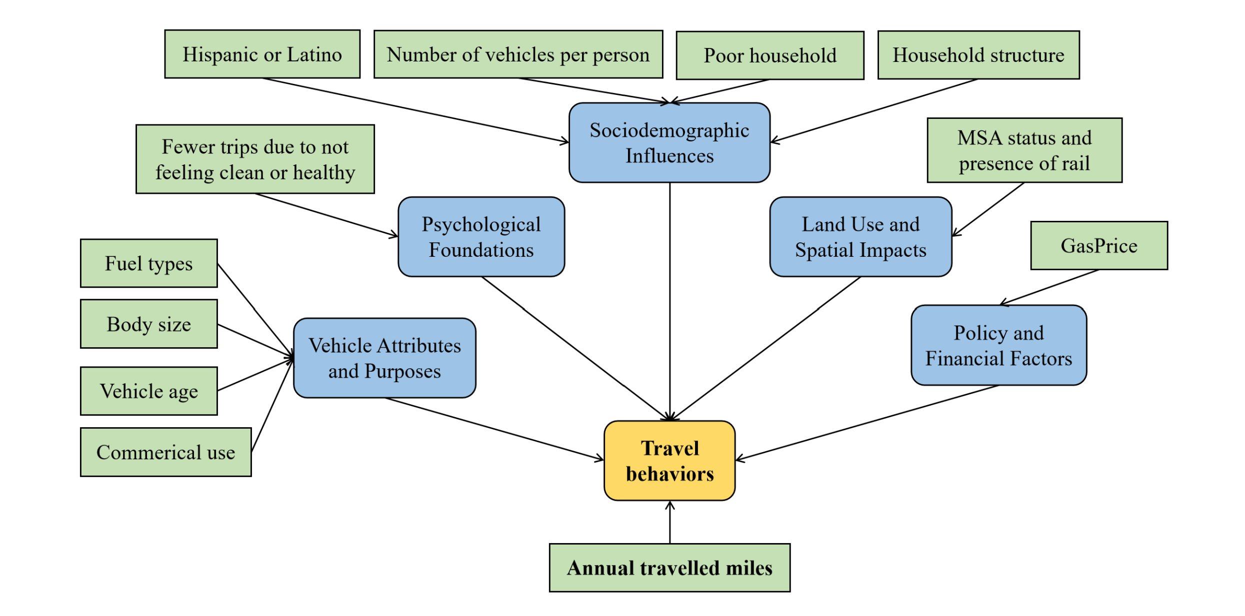

Figure 2.1 Schematic Representation of the Groups of Variables considered as explanatory variables here

Table 2.2 An example of the variables found in the 2022 NHTS data and variable description.

Variables		(% of 11,697 vehicles)
Vehicle Attributes and Type of Use	Fuel types	Gasoline (91.53%) Diesel (2.96%) Plugin (0.57%) Electric (1.38%) Hybrid (3.12%)
	Body size	Car (41.29%) SUV (30.79%) Pickup (18.20%)
	Age	Min (1.00) Median (8.00) Mean (10.21) Max (40.00)
	Commercial use	Yes (9.89%)
Psychological Foundations	Fewer trips due to not feeling clean or healthy	Yes (1.04%)
Sociodemographic Influences	Hispanic or Latino	Yes (6.82%)
	Number of vehicles per person	Min (0.25) Median (1.00) Mean (1.23) Max (17.00)
	Lower income household	Yes (3.55%)
	Household structure	Adt1_C15 (1.10%) Adt1_C21 (1.21%) Ret2 (34.15%)
Land Use and Spatial Impacts	MSA status and presence of rail	MA_MSALess1 (3.85%) WN_MSA_CMSALess1 (2.75%) SA_MSALess1 (8.77%) ES_MSA_CMSALess1 (2.12%)
Policy and Financial Factors	GasPrice	Min (272.70) Median (398.00) Mean (397.90) Max (597.9)

Note: Adt1_C15=one adult, youngest child 6-15; Adt1_C21=one adult, youngest child 16-21; Ret2=2+ adults, retired, no children; MA_MSALess1=Mid-Atlantic MSA of less than 1 million; WN_MSA_CMSALess1=West North Central MSA/CMSA of 1 million+ w/o heavy rail; SA_MSALess1=South Atlantic MSA of less than 1 million; ES_MSA_CMSALess1=East South Central MSA/CMSA of 1 million+ w/o heavy rail.

2.3 Households with one vehicle in their fleet

In the 2017 NHTS we have 30691 households with only one vehicle (Table 2.3). Of these 29527 (96.21%) are gasoline vehicles, 770 (2.5%) are hybrid and 245 (0.8%) are diesel and the rest are very small numbers of plugin hybrids, fully electric, and other unknown fuel or using some other fuel. This shows that even as early as in 2017 there were households who bought and used alternatively fueled vehicles as the only vehicle in their household. The household size distribution of the single vehicle owning households is heavily populated by single persons 21519 (70.12%). We also have a substantial number of 2 person households 6927 (22.6%). The vehicle age distribution in Table 2.3 shows the relatively young age of single car fleet with the EVs and Plugin even younger. In terms of type/size of cars sedans (typical passenger cars) are the majority of the vehicles in the single vehicle fleet households followed by the SUVs. Gasoline dominates among the sedans (60.6% of gasoline cars as sedans) and SUVs 26.2% of gasoline vehicles are SUVs). Diesel is more popular among pickup trucks with 51.8% of diesel vehicles. The annual miles are indicative of the role the type of fuel may play here. The overall average is 10300 miles and median much lower at 8000 miles showing there are a few outliers that create a skewed distribution. In fact, the highest is 200000 but there are many vehicles with just one mile recorded. There are some issues with recording annual miles in NHTS 2017 as documented by other researchers (Alberini et al., 2021). Nevertheless, Table 2.3 and Figure 2.2 show clearly that EVs not only are newer than gasoline vehicles but they are also driven less. In contrast, hybrid vehicles are driven by far more than any other fuel type except diesel. The presence of alternative to gasoline vehicles in 2017 is a good development. However, evidence from European studies shows discrepancies between expected reduction in greenhouse gas emissions and real world emissions that depend on drivers recharging behavior and/or driving styles (Fontaras et al., 2017, European Commission, 2024, Barkenbus, 2015, Fafoutelis et al., 2020).

Table 2.4 shows two regression models to test the correlation between annual vehicle miles and the factors discussed earlier. This is also a confirmation that the differences we observe in the descriptive statistics and boxplots are in fact significant differences in annual mile difference among the fuels vehicles use. Diesel and hybrid powered vehicles in 2017 are substantially and significantly higher mileage vehicles in single vehicle fleets even when we control for vehicle types, social and demographic characteristics of the owner household, and place of residence characteristics. The same conclusions are reached in the regression model that is based on the logarithm of annual miles. The rest of the variables show that as vehicle age people tend to use them less except for the difference between new vehicles and 2 years and older. Pickup trucks are the vehicles driven the most and there are similarities among SUVs and Vans, and lower use of sedans. All this is compared to vehicle types excluded from the regressions that are used as reference. The presence of children in households increase the annual miles and employment plays the positive role as expected. There are some differences among places of residence but many are not significantly different than zero indicating uniformity in annual miles accumulation across the US.

Table 2.3 Vehicle characteristics for the single vehicle fleets in NHTS 2017

	Diesel (N=245)	EV (N=26)	Gasoline (N=29527)	Hybrid (N=770)	Other (N=57)	Plugin (N=66)	Overall (N=30691)
ANNMILES							
Mean (SD)	13900 (15700)	8900 (6820)	10200 (12800)	12700 (16500)	12200 (26200)	10500 (8990)	10300 (12900)
Median [Min, Max]	11000 [150, 170000]	6830 [15.0, 26000]	8000 [1.00, 200000]	10000 [30.0, 200000]	8000 [500, 200000]	9100 [1000, 65000]	8000 [1.00, 200000]
factor(Age2to5)							
0	132 (53.9%)	4 (15.4%)	18676 (63.3%)	380 (49.4%)	34 (59.6%)	11 (16.7%)	19237 (62.7%)
1	113 (46.1%)	22 (84.6%)	10851 (36.7%)	390 (50.6%)	23 (40.4%)	55 (83.3%)	11454 (37.3%)
factor(Age6to10)							
0	202 (82.4%)	25 (96.2%)	21924 (74.3%)	502 (65.2%)	38 (66.7%)	63 (95.5%)	22754 (74.1%)
1	43 (17.6%)	1 (3.8%)	7603 (25.7%)	268 (34.8%)	19 (33.3%)	3 (4.5%)	7937 (25.9%)
factor(Age11to15)							
0	191 (78.0%)	25 (96.2%)	23106 (78.3%)	671 (87.1%)	49 (86.0%)	66 (100%)	24108 (78.6%)
1	54 (22.0%)	1 (3.8%)	6421 (21.7%)	99 (12.9%)	8 (14.0%)	0 (0%)	6583 (21.4%)
factor(Age16to20)							
0	227 (92.7%)	26 (100%)	26497 (89.7%)	765 (99.4%)	54 (94.7%)	66 (100%)	27635 (90.0%)
1	18 (7.3%)	0 (0%)	3030 (10.3%)	5 (0.6%)	3 (5.3%)	0 (0%)	3056 (10.0%)
factor(typeveh)							
Motorcycle	0 (0%)	1 (3.8%)	35 (0.1%)	0 (0%)	1 (1.8%)	0 (0%)	37 (0.1%)
Other	0 (0%)	0 (0%)	14 (0.0%)	0 (0%)	2 (3.5%)	0 (0%)	16 (0.1%)
OtherTruck	1 (0.4%)	0 (0%)	57 (0.2%)	0 (0%)	0 (0%)	0 (0%)	58 (0.2%)
Pickup	127 (51.8%)	0 (0%)	2399 (8.1%)	0 (0%)	5 (8.8%)	0 (0%)	2531 (8.2%)
RV	2 (0.8%)	0 (0%)	18 (0.1%)	1 (0.1%)	0 (0%)	0 (0%)	21 (0.1%)
Sedan	90 (36.7%)	23 (88.5%)	17895 (60.6%)	695 (90.3%)	26 (45.6%)	65 (98.5%)	18794 (61.2%)
SUV	24 (9.8%)	2 (7.7%)	7731 (26.2%)	70 (9.1%)	16 (28.1%)	1 (1.5%)	7844 (25.6%)
Van	1 (0.4%)	0 (0%)	1378 (4.7%)	4 (0.5%)	7 (12.3%)	0 (0%)	1390 (4.5%)

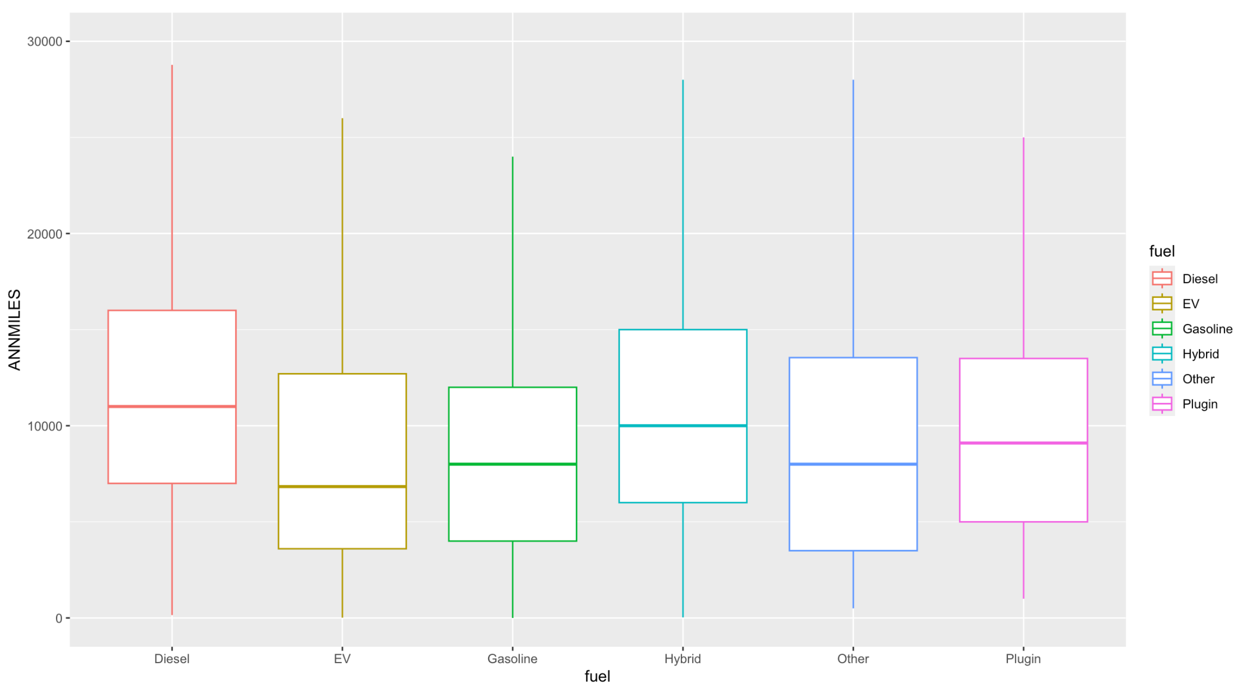

Figure 2.2 Annual miles by type of vehicle fuel in NHTS 2017 for single vehicle fleets

Note: Boxplots without showing the outliers

Table 2.4 Regression of NHTS 2017 Annual Miles of single vehicle households

	ANNMILES	log(ANNMILES)
	(1)	(2)
Diesel	2,905.73***	0.27***
	(814.04)	(0.07)
Hybrid	2,083.06***	0.19***
	(462.18)	(0.04)
Sedan	2,229.54**	0.58***
	(1,095.90)	(0.09)
SUV	2,999.73***	0.72***
	(1,101.97)	(0.09)
Van	2,578.10**	0.67***
	(1,144.50)	(0.09)
Pickup truck	4,089.11***	0.81***
	(1,120.47)	(0.09)
One year old vehicle	2,377.10***	0.58***
	(644.88)	(0.05)
Two to Five years old vehicle	4,130.34***	0.80***
	(232.93)	(0.02)
Six to Ten years old vehicle	3,072.35***	0.61***
	(243.42)	(0.02)
Eleven to Fifteen years old vehicle	1,452.03***	0.36***
	(248.85)	(0.02)
Older than 35 years old vehicle	-2,330.76*	-0.65***
	(1,352.35)	(0.11)
No employed in household	-2,862.61***	-0.50***
	(219.69)	(0.02)
Latino household	1,212.57***	-0.03
	(315.62)	(0.03)
Black household	600.58**	-0.20***
	(274.45)	(0.02)
Household size	955.25***	0.03***
	(129.95)	(0.01)
Home owning household	-649.51***	0.07***
	(157.99)	(0.01)

Table 2.4 Regression of NHTS 2017 Annual Miles of single vehicle households (continued)

One adult, youngest child 0-5	1,879.02***	0.26***
	(668.87)	(0.06)
One adult, youngest child 6-15	1,012.85**	0.21***
	(429.26)	(0.04)
2+ adults, youngest child 6-15	1,259.10*	0.02
	(684.16)	(0.06)
2+ adults, youngest child 16-21	-58.03	0.15
	(1,155.23)	(0.10)
One adult, retired, no children	-1,942.93***	-0.18***
	(243.63)	(0.02)
2+ adults, retired, no children	-1,234.61***	-0.01
	(286.29)	(0.02)
Reside in Mid-Atlantic (NY, NJ, PA) Not in a Metro area	1,199.66**	0.08**
	(472.32)	(0.04)
Reside in East North Central (IL, IN, MI, OH, WI) Not a Metro area	1,615.49***	0.12***
	(454.43)	(0.04)
Reside in West North Central (IA, KS, MO, MN, ND, NE, SD) Metro 1 million+ no heavy rail	2,008.53**	0.13*
	(933.26)	(0.08)
Reside in South Atlantic (DE, FL, GA, MD, NC, SC, WV, VA) Metro < 1 million	1,173.54***	0.06***
	(223.66)	(0.02)
Reside in South Atlantic (DE, FL, GA, MD, NC, SC, WV, VA) Not in a Metro area	1,667.37***	0.03
	(411.15)	(0.03)
Reside in East South Central MSA/CMSA of 1 million+ no heavy rail	-834.73	-0.21*
	(1,310.78)	(0.11)
Reside in West South Central MSA of less than 1 million	-170.12	-0.06**
	(362.02)	(0.03)
Constant	5,772.87***	7.80***
	(1,125.55)	(0.09)
N	30,691	30,691
R^2	0.06	0.17
Adjusted R^2	0.06	0.17
Residual Std. Error (df = 30661)	12,535.63	1.03
F Statistic (df = 29; 30661)	71.27***	216.45***

*p < .1; **p < .05; ***p < .01

In NHTS 2022 we have a much smaller sample size (2585 vehicles in single vehicle household fleets) and Table 2.5 reflects this major difference with the NHTS 2017 that includes much smaller numbers of vehicles fueled with something that is not gasoline. This has important implications when we explore correlation for Annual VMT. Table 2.5 shows the 24 diesel vehicles in this year have more than double the vehicle average in 2022. This is also clearly shown in Figure 2.3 with the boxplots without outliers shown. The median of diesel powered vehicles is very similar to the median of the electric vehicles. However, the average of the diesel cars in by far larger. Also, the average annual miles of all the non-diesel vehicles is similar and this has implications for the regression models in Table 2.6 in which only the diesel vehicles are significantly different than the rest.

Table 2.6 also shows that most vehicle types accumulate similar amounts of VMT per year in 2022 except for SUVs that have a higher Annual VMT. As in 2017 the presence of children in the household are associated with higher Annual VMT and substantially more for single parents of the very young children. Retirement is also associated with a decrease in traveling as reflected by the Annual VMT but in 2022 this appears only for a single retiree. In addition, a much smaller number of places of residence show significant differences in 2022 than in 2017. However, it should be note that higher sample sizes in regressions models tend to show higher significance for even small differences in the data. In the next section we explore these relationships in fleets with two or more vehicles.

Table 2.5 Vehicle characteristics for the single vehicle fleets in NHTS 2022

	Diesel (N=24)	EV (N=24)	Gasoline (N=2409)	Hybrid (N=107)	Other (N=8)	Plugin (N=13)	Overall (N=2585)
ANNMILES							
Mean (SD)	36100 (57300)	14500 (12600)	16500 (32800)	12700 (21700)	20900 (54200)	7560 (3820)	16500 (32700)
Median [Min, Max]	12000 [12.0, 200000]	12000 [150, 53500]	8000 [1.00, 200000]	8000 [100, 158000]	1500 [200, 155000]	7500 [1700, 15000]	8000 [1.00, 200000]
factor(Age2to5)							
0	20 (83.3%)	3 (12.5%)	1767 (73.4%)	62 (57.9%)	6 (75.0%)	5 (38.5%)	1863 (72.1%)
1	4 (16.7%)	21 (87.5%)	642 (26.7%)	45 (42.1%)	2 (25.0%)	8 (61.5%)	722 (27.9%)
factor(Age6to10)							
0	14 (58.3%)	21 (87.5%)	1629 (67.6%)	79 (73.8%)	6 (75.0%)	10 (76.9%)	1759 (68.0%)
1	10 (41.7%)	3 (12.5%)	780 (32.4%)	28 (26.2%)	2 (25.0%)	3 (23.1%)	826 (32.0%)
factor(Age11to15)							
0	22 (91.7%)	24 (100%)	1950 (80.9%)	82 (76.6%)	7 (87.5%)	12 (92.3%)	2097 (81.1%)
1	2 (8.3%)	0 (0%)	459 (19.1%)	25 (23.4%)	1 (12.5%)	1 (7.7%)	488 (18.9%)
factor(Age16to20)							
0	20 (83.3%)	24 (100%)	2086 (86.6%)	98 (91.6%)	6 (75.0%)	13 (100%)	2247 (86.9%)
1	4 (16.7%)	0 (0%)	323 (13.4%)	9 (8.4%)	2 (25.0%)	0 (0%)	338 (13.1%)
factor(typeveh)							
Motorcycle	0 (0%)	0 (0%)	2 (0.1%)	0 (0%)	0 (0%)	0 (0%)	2 (0.1%)
Other	1 (4.2%)	1 (4.2%)	0 (0%)	0 (0%)	1 (12.5%)	0 (0%)	3 (0.1%)
OtherTruck	3 (12.5%)	0 (0%)	4 (0.2%)	0 (0%)	0 (0%)	0 (0%)	7 (0.3%)
Pickup	11 (45.8%)	0 (0%)	190 (7.9%)	1 (0.9%)	0 (0%)	0 (0%)	202 (7.8%)
Sedan	7 (29.2%)	17 (70.8%)	1287 (53.4%)	78 (72.9%)	4 (50.0%)	9 (69.2%)	1402 (54.2%)
SUV	2 (8.3%)	6 (25.0%)	837 (34.7%)	26 (24.3%)	3 (37.5%)	4 (30.8%)	878 (34.0%)
Van	0 (0%)	0 (0%)	89 (3.7%)	2 (1.9%)	0 (0%)	0 (0%)	91 (3.5%)

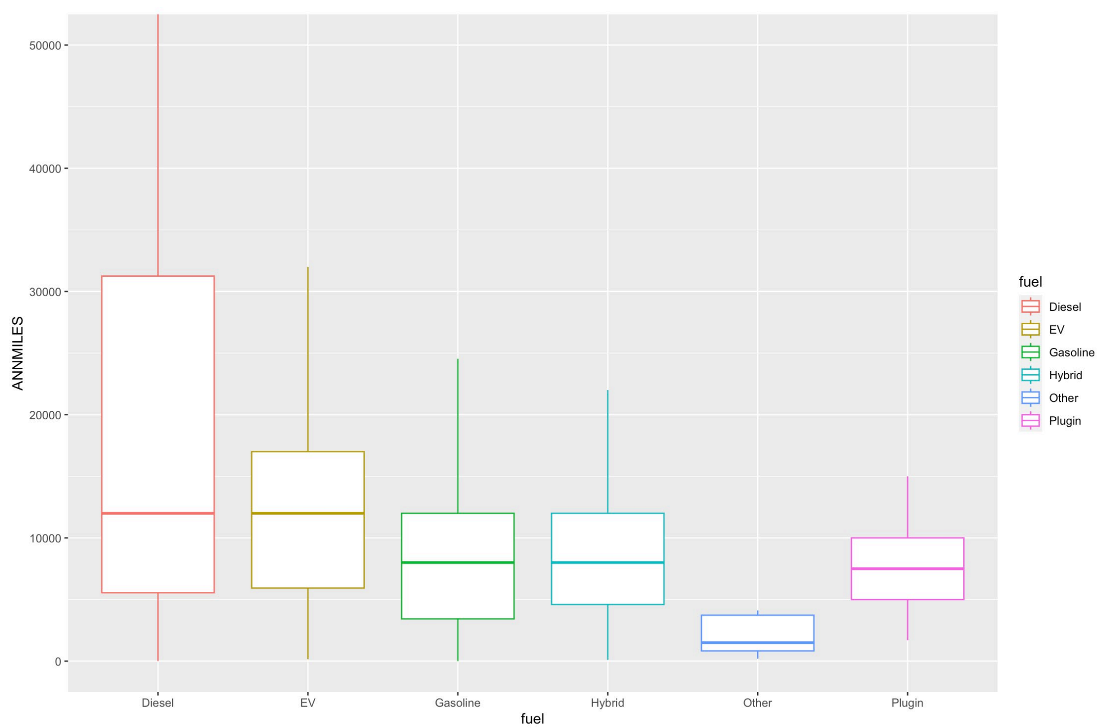

Figure 2.3 Annual miles by type of vehicle fuel in NHTS 2017 for single vehicle fleets

Table 2.6 Regression of NHTS 2022 Annual Miles of single vehicle households

	ANNMILES	log(ANNMILES)
Diesel	16,481.99**	0.23
	(6,633.70)	(0.30)
SUV	293.21	0.18***
	(1,391.30)	(0.06)
Pickup truck	2,222.53	0.36***
	(2,456.04)	(0.11)
Two to Five years old vehicle	-7,806.47***	0.37***
	(1,862.76)	(0.09)
Six to Ten years old vehicle	-5,036.63***	0.32***
	(1,801.47)	(0.08)
Eleven to Fifteen years old vehicle	-1,802.22	0.28***
	(2,018.80)	(0.09)
Older than 35 years old vehicle	-11,301.35	-0.73*
	(9,014.99)	(0.41)
No employed in household	-82.64	-0.38***
	(1,459.13)	(0.07)
Latino household	2,848.75	-0.20*
	(2,362.89)	(0.11)
Black household	6,643.60***	-0.21**
	(2,243.20)	(0.10)
Household size	-2,123.66***	-0.16***
	(820.03)	(0.04)
One adult, youngest child 0-5	22,631.19***	0.95***
	(5,360.52)	(0.25)
One adult, youngest child 6-15	16,536.23***	0.68***
	(3,255.86)	(0.15)
2+ adults, youngest child 6-15	8,094.89**	0.51***
	(4,108.27)	(0.19)
2+ adults, youngest child 16-21	18,491.16**	0.59
	(8,187.99)	(0.37)
One adult, retired, no children	-4,617.49***	-0.21***
	(1,754.60)	(0.08)
Reside in Mid-Atlantic (NY, NJ, PA) Not in a Metro area	40,753.57**	0.90
	(16,022.16)	(0.73)
Reside in South Atlantic (DE, FL, GA, MD, NC, SC, WV, VA) Not in a Metro area	20,538.15***	0.66**
	(6,586.25)	(0.30)
Reside in West South Central MSA of less than 1 million	10,464.42***	0.45***
	(3,023.20)	(0.14)
Constant	21,962.41***	8.84***
	(2,141.44)	(0.10)
N	2,585	2,585
R^2 (Adjusted R^2)	0.05 (0.05)	0.07(0.06)
Residual Std. Error (df = 2565)	31,911.84	1.46
F Statistic (df = 19; 2565)	7.47***	9.58***

*p < .1; **p < .05; ***p < .01

2.4 Vehicles in Multivehicle Household Fleets

Households with two or more vehicles may have a different allocation of VMT to each vehicle that depends on within household task allocation, preference of individual household members, history of vehicle use, and a variety of other factors. This makes VMT accumulated on one vehicle correlated with VMT accumulated on another for observable and unobservable reasons. If one does not account for this interdependency regression coefficients estimates tend to be biased and inferences based on them incorrect. In this section we repeat the analysis of the single vehicle fleet for the multiple vehicle household fleets. Table 2.7 shows annual VMT by fuel type, fleet age and composition in terms of vehicle types. The per vehicle annual VMT is much lower when households own two or more cars. In 2017, electric cars were used at lower levels that hybrid and plugin hybrid cars. Sedan (car) is the highest number of vehicles followed by SUVs and then pickup trucks. Figure 2.4 shows the median of hybrid and plugin vehicles as higher and the diesel vehicles having a higher variance. It is notable the similarity of the Annual VMT distribution among all vehicles in 2017. This is confirmed by the regression models presented next in Table 2.8.

To compare vehicle utilization in vehicle fleets of one vehicle versus multiple vehicles, the VMT per vehicle regression models are specific using the same variables. The third column of coefficients in Table 2.8 is the multilevel VMT regression and that is the correct one to use for the multiple vehicle VMT because the ICC is 0.15 and significant. Also, accounting for the multilevel nature of the data shows a better fit. The differences among fuels that we observed with descriptive statistics and boxplots are reflected here in terms of significant coefficients that are positive for the single vehicle fleets but negative for the multiple vehicle fleets. This shows the fuel type motivates different utilization when in the presence of other options of vehicles for the households. This is also a reflection of the lower VMT per vehicle when multiple vehicles are available. In fact, the ratio of vehicles over household size also captures the impact of more vehicles available to household member with a negative significant coefficient.

Vehicle types are also significant in VMT contribution with pickup trucks consistently higher than other types either when the solo vehicle in the fleet or with other vehicles. The negative coefficient of the vehicle age shows that older vehicles are used less. Ethnicity also shows significance in these models with Latino household accumulating a higher number of VMT but much lower per vehicle when multiple vehicles are available. The poverty level has a significant impact on VMT but reversed between single vehicle and multiple vehicle households presumably due to different ways of using the vehicles. Couples of retired persons show a significant and substantially lower VMT than all other household types. The place of residence is influential in these models as in the earlier models but requires added spatial analysis to discern the reasons. In these models the gasoline price is used and shows that higher gasoline prices are negatively correlated with Annual VMT. It should be note this is the average gasoline price reported by respondents on the interview days and not the entire year, and most likely it captures regional differences in gasoline prices that are due to local taxation and distribution costs.

Table 2.7 Vehicle characteristics for the multiple vehicle fleets in NHTS 2017

	Diesel (N=5291)	EV (N=450)	Gasoline (N=145819)	Hybrid (N=3187)	Other (N=367)	Plugin (N=344)	Overall (N=155458)
ANNMILES							
Mean (SD)	11200 (16300)	8160 (11800)	9450 (11800)	12900 (11200)	12000 (23500)	11600 (14700)	9590 (12000)
Median [Min, Max]	7200 [2.00, 200000]	7200 [5.00, 200000]	7800 [1.00, 200000]	11000 [4.00, 200000]	8000 [2.00, 200000]	10000 [10.0, 200000]	8000 [1.00, 200000]
factor(Age2to5)							
0	3806 (71.9%)	93 (20.7%)	98563 (67.6%)	1487 (46.7%)	230 (62.7%)	66 (19.2%)	104245 (67.1%)
1	1485 (28.1%)	357 (79.3%)	47256 (32.4%)	1700 (53.3%)	137 (37.3%)	278 (80.8%)	51213 (32.9%)
factor(Age6to10)							
0	4382 (82.8%)	404 (89.8%)	111566 (76.5%)	2114 (66.3%)	275 (74.9%)	324 (94.2%)	119065 (76.6%)
1	909 (17.2%)	46 (10.2%)	34253 (23.5%)	1073 (33.7%)	92 (25.1%)	20 (5.8%)	36393 (23.4%)
factor(Age11to15)							
0	3810 (72.0%)	438 (97.3%)	114260 (78.4%)	2851 (89.5%)	337 (91.8%)	339 (98.5%)	122035 (78.5%)
1	1481 (28.0%)	12 (2.7%)	31559 (21.6%)	336 (10.5%)	30 (8.2%)	5 (1.5%)	33423 (21.5%)
factor(Age16to20)							
0	4510 (85.2%)	439 (97.6%)	128825 (88.3%)	3168 (99.4%)	348 (94.8%)	342 (99.4%)	137632 (88.5%)
1	781 (14.8%)	11 (2.4%)	16994 (11.7%)	19 (0.6%)	19 (5.2%)	2 (0.6%)	17826 (11.5%)
factor(car)							
0	4458 (84.3%)	80 (17.8%)	80767 (55.4%)	376 (11.8%)	237 (64.6%)	30 (8.7%)	85948 (55.3%)
1	833 (15.7%)	370 (82.2%)	65052 (44.6%)	2811 (88.2%)	130 (35.4%)	314 (91.3%)	69510 (44.7%)
factor(suv)							
0	5001 (94.5%)	440 (97.8%)	109213 (74.9%)	2832 (88.9%)	308 (83.9%)	325 (94.5%)	118119 (76.0%)
1	290 (5.5%)	10 (2.2%)	36606 (25.1%)	355 (11.1%)	59 (16.1%)	19 (5.5%)	37339 (24.0%)
factor(pickup)							
0	1748 (33.0%)	450 (100%)	118050 (81.0%)	3181 (99.8%)	292 (79.6%)	344 (100%)	124065 (79.8%)
1	3543 (67.0%)	0 (0%)	27769 (19.0%)	6 (0.2%)	75 (20.4%)	0 (0%)	31393 (20.2%)

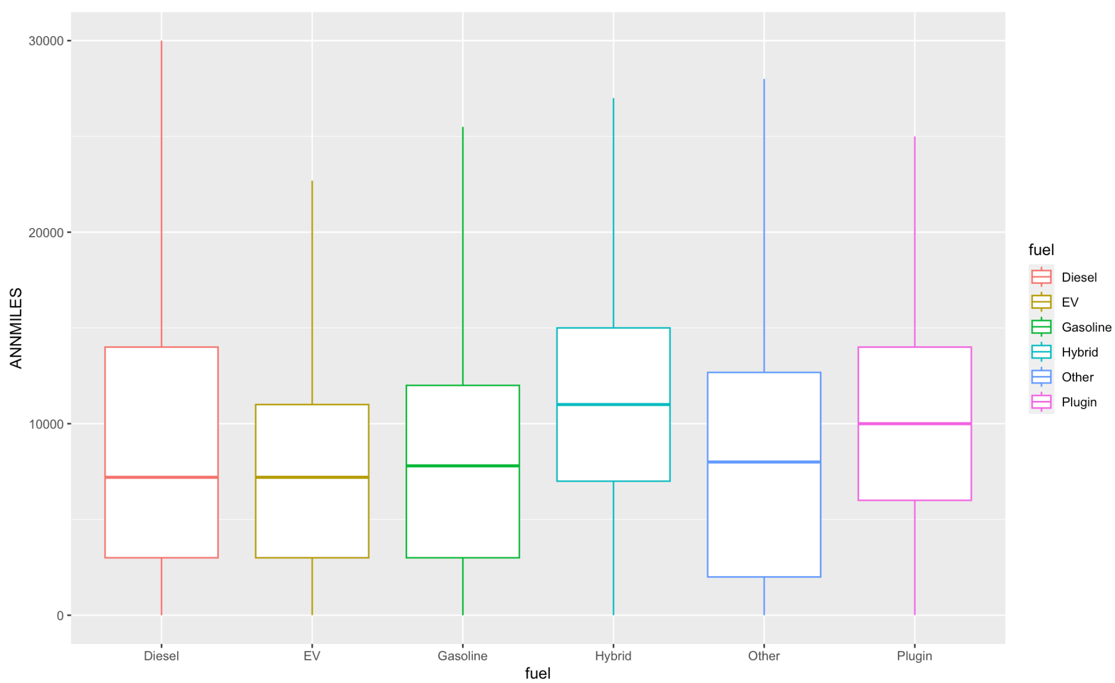

Figure 2.4 Annual miles by type of vehicle fuel in NHTS 2017 for single vehicle fleets

Table 2.8 Regression of NHTS 2017 Annual Miles of single and multiple vehicle households

	Linear Single vehicle fleet 2017)	**Linear Multiple vehicle fleet 2017)**	**Multilevel Multiple vehicle fleet 2017)**
Predictors	*Estimates*	*Estimates*	*Estimates*
(Intercept)	19950.61 ***	19710.41 ***	19821.89 ***
Gasoline	2561.25	-2797.17 ***	-2733.41 ***
Diesel	5641.45 **	-247.72	-238.50
Hybrid	4337.02 *	-1662.76 *	-1460.81 *
Sedan	260.41	2022.14 ***	2077.07 ***
SUV	919.21 **	2710.49 ***	2755.18 ***
Pickup	2184.94 ***	2099.70 ***	2084.76 ***
Vehicle age in years	-258.51 ***	-314.92 ***	-324.16 ***
Latino	1496.75 ***	162.37	210.12
Ratio of vehicle over household size	-7327.17 ***	-1087.00 ***	-1190.00 ***
Household below poverty	-488.22 *	377.98 **	389.65 **
Two adults retired with no children	-3912.65 ***	-2724.09 ***	-2777.55 ***
Reside in West North Central (IA, KS, MO, MN, ND, NE, SD) Metro 1 million+ no heavy rail	1896.79 **	153.81	154.04
Reside in South Atlantic (DE, FL, GA, MD, NC, SC, WV, VA) Metro < 1 million	891.84 ***	324.47 ***	370.63 ***
GasPrice[(1)]	-17.21 ***	-16.00 ***	-15.88 ***
Random Effects			
σ^2			113174621.65
τ_{00}			19604314.26 HOUSEID
ICC			0.15
N			67680 HOUSEID
Observations	30691	155458	155458
R^2 / R^2 adjusted	0.037 / 0.037	0.086 / 0.086	0.091 / 0.225

*Notes (1) GasPrice is the within household average of gasoline price for all persons on the interview day. For the households with no data on this the mean was used imputed. * p<0.1 ** p<0.05 *** p<0.01*

Table 2.9 shows annual VMT by fuel type, fleet age and composition in terms of vehicle types. The per vehicle annual VMT is much lower when households own two or more cars. In 2022, electric cars were used at lower levels than gasoline, diesel, hybrid and plugin hybrid cars. Sedan (car) is the highest number of vehicles followed by SUVs and then pickup trucks. Figure 2.5 shows the median and variance differences among all fuels with the 5 biodiesel off the charts. It is notable the similarity of the Annual VMT distribution among all vehicles in 2022. This is confirmed by the regression models presented next in Table 2.10.

Similarly to 2017, we compare vehicle use in vehicle fleets of one vehicle versus multiple vehicles, the VMT per vehicle regression models are specified using the same variables. The third column of coefficients in Table 2.10 is the multilevel VMT regression and that is the correct one to use for the multiple vehicle VMT because the ICC is 0.50 and significant. Also, accounting for the multilevel nature of the data shows a better fit. The differences among fuels that we observe with descriptive statistics and boxplots are captured here with coefficients that are significant only for diesel vehicles that are used for a higher VMT than all other fuels. This shows the fuel type motivates different use when in the presence of other options of vehicles for the households. This is also a reflection of the lower VMT per vehicle when multiple vehicles are available. In fact, the ratio of vehicles over household size also captures the impact of more vehicles available to household member with a larger negative significant coefficient in the third column of Table 2.10.

Vehicle types are also significant in VMT contribution with pickup trucks higher than other types when in the solo vehicle in the fleet but lower than Sedans and SUV when in fleets with other vehicles. This is different from the NHTS 2017 data. The positive coefficient in the single vehicle fleet turns to negative in the multiple vehicle fleet indicating that when available newer vehicles are used more often. Ethnicity also shows significance in these models with Latino households accumulating a higher number of VMT and even much higher per vehicle when multiple vehicles are available. The poverty level has a significant impact on VMT and consistently high in single vehicle and multiple vehicle households presumably due to different ways of using the vehicles. This is also happening for vehicles used for commercial purposes.

Couples of retired persons show a significant and substantially lower VMT than all other household types. In contrast, the vehicles of single parents are accumulating by far higher VMT per year than other life households. The place of residence is influential in these models as in the earlier models and shows reversal of the coefficient sign between single vehicle fleet and multiple vehicle fleets. This also requires added spatial analysis to discern the reasons and again indicates changes from 2017. The gasoline price is also used in the 2022 models and shows that higher gasoline prices are negatively correlated with Annual VMT. The computation of this variable was done in the same way as in 2017.

Table 2.9 Vehicle characteristics for the multiple vehicle fleets in NHTS 2022

	Biodiesel (N=5)	Diesel (N=341)	Electric Only (N=161)	Gasoline (N=10706)	Hybrid (N=365)	Other (N=31)	Plug-in Hybrid (N=67)	Unknown (N=21)	Overall (N=11697)
ANNMILES									
Mean (SD)	61700 (81400)	12900 (27000)	9480 (13300)	12500 (25500)	11800 (17000)	2210 (5510)	12600 (15900)	8250 (7840)	12500 (25100)
Median [Min, Max]	20000 [4000, 200000]	5330 [3.00, 200000]	7610 [4.00, 150000]	6000 [1.00, 200000]	8000 [15.0, 159000]	204 [25.0, 28000]	9000 [400, 111000]	5000 [350, 25000]	6300 [1.00, 200000]
factor(Age2to5)									
0	4 (80.0%)	262 (76.8%)	44 (27.3%)	8040 (75.1%)	218 (59.7%)	8 (25.8%)	32 (47.8%)	12 (57.1%)	8620 (73.7%)
1	1 (20.0%)	79 (23.2%)	117 (72.7%)	2666 (24.9%)	147 (40.3%)	23 (74.2%)	35 (52.2%)	9 (42.9%)	3077 (26.3%)
factor(Age6to10)									
0	4 (80.0%)	247 (72.4%)	130 (80.7%)	7456 (69.6%)	230 (63.0%)	29 (93.5%)	39 (58.2%)	18 (85.7%)	8153 (69.7%)
1	1 (20.0%)	94 (27.6%)	31 (19.3%)	3250 (30.4%)	135 (37.0%)	2 (6.5%)	28 (41.8%)	3 (14.3%)	3544 (30.3%)
factor(Age11to15)									
0	5 (100%)	290 (85.0%)	157 (97.5%)	8736 (81.6%)	301 (82.5%)	28 (90.3%)	65 (97.0%)	17 (81.0%)	9599 (82.1%)
1	0 (0%)	51 (15.0%)	4 (2.5%)	1970 (18.4%)	64 (17.5%)	3 (9.7%)	2 (3.0%)	4 (19.0%)	2098 (17.9%)
factor(Age16to20)									
0	4 (80.0%)	293 (85.9%)	159 (98.8%)	9252 (86.4%)	349 (95.6%)	30 (96.8%)	67 (100%)	16 (76.2%)	10170 (86.9%)
1	1 (20.0%)	48 (14.1%)	2 (1.2%)	1454 (13.6%)	16 (4.4%)	1 (3.2%)	0 (0%)	5 (23.8%)	1527 (13.1%)
factor(car)									
0	5 (100%)	308 (90.3%)	45 (28.0%)	6338 (59.2%)	107 (29.3%)	27 (87.1%)	25 (37.3%)	12 (57.1%)	6867 (58.7%)
1	0 (0%)	33 (9.7%)	116 (72.0%)	4368 (40.8%)	258 (70.7%)	4 (12.9%)	42 (62.7%)	9 (42.9%)	4830 (41.3%)
factor(suv)									
0	5 (100%)	325 (95.3%)	137 (85.1%)	7260 (67.8%)	273 (74.8%)	31 (100%)	48 (71.6%)	17 (81.0%)	8096 (69.2%)
1	0 (0%)	16 (4.7%)	24 (14.9%)	3446 (32.2%)	92 (25.2%)	0 (0%)	19 (28.4%)	4 (19.0%)	3601 (30.8%)
factor(pickup)									
0	1 (20.0%)	84 (24.6%)	159 (98.8%)	8852 (82.7%)	358 (98.1%)	29 (93.5%)	67 (100%)	18 (85.7%)	9568 (81.8%)
1	4 (80.0%)	257 (75.4%)	2 (1.2%)	1854 (17.3%)	7 (1.9%)	2 (6.5%)	0 (0%)	3 (14.3%)	2129 (18.2%)

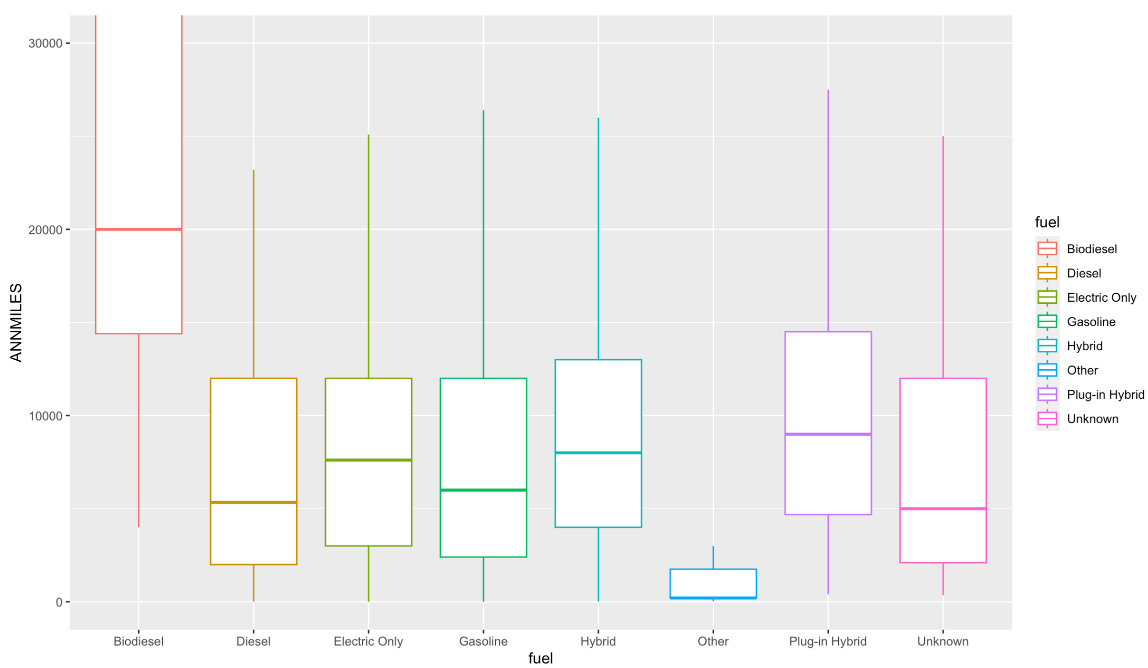

Figure 2.5 Annual miles by type of vehicle fuel in NHTS 2017 for single vehicle fleets

Table 2.10 Regression of NHTS 2022 Annual Miles of single and multiple vehicle households

	Linear Single vehicle fleet 2022	**Linear Multiple vehicle fleet 2022**	**Linear Multilevel Multiple vehicle fleet 2022**
Predictors	*Estimates*	*Estimates*	*Estimates*
(Intercept)	16635.95 ***	16911.70 ***	18407.97 ***
Diesel	18307.22 ***	2047.74	1805.99
Car	509.45	3003.75 ***	2112.19 ***
Suv	812.24	3126.42 ***	2768.64 ***
Pickup	2028.81	2551.85 ***	2231.26 ***
Vehicle age in years	297.84 ***	-52.62 *	-124.53 ***
Vehicle used for commerce	2968.78	3425.69 ***	5275.82 ***
Latino	3681.29	4731.64 ***	4469.93 ***
Ratio of vehicles over household size	-472.07	-1844.48 ***	-2329.15 ***
Household below poverty	6788.80 ***	4444.18 ***	5093.00 ***
Single adult youngest child 6-15	14773.49 ***	8455.54 ***	10860.90 ***
Single adult youngest child 16-21	5139.21	7082.00 ***	8560.23 ***
Two adults retired with no children	-2478.97	-4912.83 ***	-4982.76 ***
Reside in Mid-Atlantic MSA of less than 1 million	713.44	3095.13 ***	3216.28 **
Reside in West North Central MSA/CMSA of 1 million+ w/o heavy rail	-3159.77	5768.81 ***	5126.18 ***
Reside in South Atlantic MSA of less than 1 million	-799.17	2326.24 ***	2299.89 **
Reside in East South Central MSA/CMSA of 1 million+ w/o heavy rail	7458.40	3125.05 *	3751.64 *
GasPrice(1)	-12.56	-10.69 ***	-10.01 **
Random Effects			
σ^2			307733102.64
τ_{00}			311488649.82 HOUSEID
ICC			0.50
N			4738 HOUSEID
Observations	2585	11697	11697
R^2 / R^2 adjusted	0.030 / 0.024	0.030 / 0.029	0.039 / 0.522

*Notes (1) GasPrice is the within household average of gasoline price for all persons on the interview day. For the households with no data on this the mean was used imputed. * p<0.1 ** p<0.05 *** p<0.01*

3. Part 3 Analysis of Hypothetical Choice Scenarios

3.1 Data

In this section we analyze the California Energy Commission household vehicle stated preference (SP) questionnaire data. These are also known as hypothetical choice scenario data and discrete choice experiments. The primary goal of this type of data collection is to show the items necessary for estimating utility functions and to establish discrete choice (and related) models for forecasting. In this survey, each person representing a household is subjected to eight "experiments." Each experiment offers four alternatives and the respondent select one of the four options. This means that persons chose one of four options in a repeated choice process eight times based on various combinations. In the survey of 2019 (the latest available from CEC), the characteristics that varied among the options are vehicle type, vehicle make/model, model year, fuel type, maintenance cost, miles per gallon equivalent (MPGe), vehicle range, vehicle price, and so forth. The database used in this section is one component of the same database used in Part 1 of this report. In this section we focus on the discrete choice experiment in 2019.

This type of data can be analyzed using discrete choice models designed for random utility. These are in essence nonlinear regression models that when one includes the price of an option in the utility function that can be then used to derive willingness to pay (WTP) for different vehicle attributes. This is an essential part in policy analysis that measures the amount a decision-maker is willing to pay for a particular product attribute or service level. This parameter quantifies the trade-off people accept between the attribute's cost and value. As an illustration, the WTP of vehicle range with regard to vehicle price is the coefficient of vehicle range derived from the utility function divided by the coefficient of the vehicle price.

The objective of the discrete choice model is to provide a representation of the decision-making process and to generate a probability for each available option. The decision-maker is expected to select only one option from the four options offered. It presupposes that decision-makers make well-informed choices by weighing their preferences against the characteristics of the available options. This analysis, which captures the decision-maker's subjective evaluation of the alternatives and reflects their preferences and trade-offs, relies heavily on utility functions (Hensher et al., 2015). The greater the utility value of an alternative, the more the decision-maker prefers it. In general, its formula is as follows:

$$U_{ij} = F(x_i, z_j, e_{ij})$$

Specifically, the utility (U_{ij}) of a person i is a function of individual/household observed characteristics (x_i), the observed characteristics of the alternative j (z_j), and an error term indicating unobserved attributes of both alternatives and the person (e_{ij}). To simplify the estimate, the utility function (F) is typically assumed to be linear. The assumed distribution of the random e_{ij} provides the functional form (e.g., Logit or Probit) of the probability of selecting an option/alternative. In this application we assume an extreme value distribution that implies the probability of choice is a closed form function of the systematic portion of the random utilities of each of the four options here.

3.2 CVS 2019 vehicle choice estimates

Considering the substantial differences found between single vehicle household fleets and multiple vehicle household fleets in this section separate discrete choice models are estimated depending on the level of car ownership. Table 3.1 presents coefficient estimates from discrete choice models estimated separately for households with one vehicle (*single vehicle household fleet*), two vehicles (*two vehicle household fleet*), and three or more vehicles (Three or more vehicle household fleet). These models assess the influence of vehicle attributes, policy incentives, and socio-economic factors on vehicle choice decisions. In general, attributes such as vehicle size and type (e.g., medium-sized vehicle SUV), tax credits, higher driving range, lower fuel costs, and greater fuel efficiency (MPG) are associated with increased utility and higher likelihood of selection. Conversely, factors such as longer refueling times, higher vehicle prices, older used vehicles, and increased fuel station distance have negative impacts on choice probability. In Table 3.1 positive coefficients show a desirable attribute and for continuous variables the coefficient shows the utility increase for a unit increase in the attribute. The opposite happens for negative coefficients. For attributes that are categories such as the fuel type and vehicle size/type all coefficients are relative to the absent categories from the utility specification. As mentioned earlier Table 3.1 shows the coefficient estimates for the three distinct utility groups for each household segment based on household fleet size.

The coefficients of the utility functions in Table 3.1 show a preference for compact and midsize sedans and SUVs as well as sports cars (positive coefficient estimates), but not for large vans and SUVs (negative coefficient estimates). Pickup trucks have also significant negative coefficients for the single vehicle households but either same insignificant for the other two groups except for large pickup trucks for the 3 or more vehicle fleet household that shows a positive and significant coefficient. The influence on the utility of zero-emission vehicles (ZEVs) is consistently lower than the internal combustion engine vehicles using gasoline (all coefficients are negative compared to the absent gasoline powered vehicles that implies they have zero coefficient). The utility also differs substantially by ownership group. It is notable, however, that the coefficients for battery electric vehicles for households who have 2 vehicles and 3 or more are not significantly different than zero and this makes this type of vehicle of the same utility as a gasoline ICE vehicle. All coefficients for used cars are negative and significant showing that new vehicles are preferred by the respondents in this survey ceteris paribus.

Most of the incentives in Table 3.1 have the expected signs but in some cases are significant different from zero showing indifference of the respondents to some of these incentives particularly when they have more than one vehicle in the household fleet. The same happens for the coefficients of range and efficiency (MPGe) showing that better performance makes the vehicles more attractive. Acceleration, however, is important only for the household spokesperson of more than 3 vehicle fleets. The costs in the utility have negative coefficients as expected and they are all significantly different than zero for annual maintenance, fuel cost and vehicle price). Time expenditures for refueling/recharging is also negative and significant for all fleet sizes. The fuel station distance from home is only important for more than 2 vehcile fleet owners. We also see important interactions between vehicle size and vehicle fuel with large electric vehicles more attractive for the single vehicle household fleet owners and the opposite for the 3 or more household fleet owners.

Table 3.1 Estimates from discrete choice models across different car ownership groups

	Dependent variable: Choice among four offered		
	Single vehicle fleet	Two vehicle fleet	Three or more vehicles fleet
Option Order:2	-0.978***	-1.034***	-0.995***
Option Order:3	-1.235***	-1.298***	-1.248***
Option Order:4	-1.395***	-1.506***	-1.414***
Compact car	0.416***	0.195***	0.397***
Midsize car	0.259***	0.324***	0.420***
Large car	-0.327***	-0.086	0.037
Sports car	0.130	0.208***	0.191*
Compact Crossover SUV	0.396***	0.560***	0.659***
Midsize Crossover SUV	0.366***	0.667***	0.697***
Large SUV	-0.549***	-0.104	0.110
Small van	-0.649***	-0.249***	-0.194*
Large van	-0.721***	-0.442***	-0.304**
Small Pickup Truck	-0.306***	-0.012	0.028
Large Pickup Truck	-0.535***	-0.018	0.237**
Gasoline Hybrid Elec. Vehicle	-0.477***	-0.487***	-0.588***
Plugin Hybrid Elec. Vehicle	-0.721***	-0.423***	-0.331*
Diesel	-1.288***	-1.234***	-0.973***
Battery Elect. Vehicle	-0.655***	-0.040	-0.026
Fuel Cell Elect. Vehicle	-0.823***	-0.290***	-0.365**
Plugin Fuel Cell Elect. Vehicle	-1.071***	-0.463***	-0.623***
Flexible Fuel	-0.410***	-0.396***	-0.320***
Used 3 Years Old	-0.419***	-0.461***	-0.294***
Used More than 3 Years old	-0.452***	-0.537***	-0.319***
HOV access for 3 years	0.126*	0.228***	0.141
Cash Rebate (amount in $)	0.193***	0.032	-0.028
Tax Credit (amount in $)	0.320***	0.329***	0.253***
Fuel Station distance from home	-0.003	-0.011***	-0.009**
Fuel/Electric Range in miles	0.001***	0.002***	0.002***
Annual Maintenance in $	-0.0004***	-0.0001***	-0.0003***
Fuel Cost per 100 miles	-0.018***	-0.015***	-0.015***
Miles Per Gallon & equivalent	0.003***	0.004***	0.003**
Acceleration (seconds from 0-60mph)	0.003	0.004	-0.026**
Refuel/recharging time for 100 miles in minutes	-0.0004	-0.0004**	-0.0002
Vehicle Price in $ /1000	-0.008***	-0.012***	-0.005***
Medium size & Any Electric Vehicle	-0.145**	-0.345***	-0.336***
Large size & Any Electric Vehicle	0.195**	-0.050	-0.407***
Observations	12,232	13,704	7,152
R^2	0.068	0.065	0.058
Log Likelihood	-12,108.710	-13,606.860	-7,411.216
LR Test (df = 36)	1,758.543***	1,878.719***	904.317***
Note:			*p<0.1; **p<0.05; ***p<0.01

Note: Vehicle Price are divided by 1,000 to yield larger and more interpretable coefficient values.

3.3 Willingness to Pay for 2019 household fleets

Table 3.2 reports willingness to pay (WTP) estimates derived from discrete choice models segmented by household vehicle ownership status: one vehicle, two vehicles, and three or more vehicles. WTP values represent the monetary value (in USD) that households are willing to pay for various vehicle attributes, holding other factors constant. The values on this table are the ratios of the estimated coefficients in Table 3.1. The denominator is the coefficient of the vehicle price multiplied by 1000 and the numerator is the corresponding coefficient of the attribute we analyze. In Table 3.2 positive means the amount respondents are willing to pay for a unit increase in that attribute.

Respondents in this survey are willing to pay different amounts to decrease annual maintenance costs with the three or more vehicle fleet owners the highest, followed by the single fleet owners and then the two vehicle fleet owners. Similar tendency we find for the willingness to pay to decrease the fuel costs per 100 miles. Fuel efficiency is valued highly by all three groups with the 3 or more fleet owners willing to pay $590 for each added MPGe, followed by $354 of the single vehicle owners, and then $317 by the two vehicle owners. The range shows the value of each added mile of a range is approximately $150 for single vehicle and two vehicle fleet owners but by far higher for the 3 or more vehicle owners that is $401. This means the WTP to pay to add 100 miles to the range of a vehicle considered for purchase varies from $15,000 to $40,000 and this is by far higher than the difference in vehicle prices with higher ranges. Refueling/recharging time for 100 miles shows the highest willingness to pay for one minute decrease for the 3 or more vehicle household fleet owners to be $51, $44 for the single vehicle fleet owners, and the lowest is approximately $35 for the two vehicle fleet owners. Reduction by one hour for charging a battery and allow a driver to travel at least 100 miles according to these estimates ranges between a WTP of $2,100 and $3,060 and this is higher than the added cost to install fast chargers at homes or to charge vehicles in fast public chargers. This shows in 2019 vehicle owners considered paying much higher vehicle prices than the supply of ranges and efficiencies in the market today.

Table 3.2 Estimates of Willingness to Pay (WTP) from discrete choice models across different car ownership groups

Attribute	Single vehicle fleet	Two vehicle fleet	Three or more vehicles fleet
Annual Maintenance in $	-44.5	-10.49	-72.31
Fuel Cost per 100 miles	-2167.39	-1202.63	-3276.33
Miles Per Gallon & equivalent	353.91	317.1	590.13
Fuel/Electric Range in miles	151.19	149.02	401.25
Refuel/recharging time for 100 miles in minutes	-44.05	-34.68	-51.14

Note: Vehicle Price in the denominator of WTP has been converted back to its original scale by multiplying by 1,000 for clearer interpretation.

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Data Management Plan

Basic Information

Principal Investigator: Konstadinos G. Goulias
Other Participants in Research Activities: Hui Shi (PhD graduate in Geography at UCSB)

Aim of Data Management Plan

To share high quality metadata with the scientific community.

Products of Research

The products we developed in this project are:

Raw Data Used towards Publication

1. Shi, H., & Goulias, K. G. (2025). Are past ownership experience and satisfaction major determinants of endorsement and future demand for zero emission vehicle technology when accounting for vehicle characteristics?. *Research in Transportation Economics*, *110*, 101535. https://doi.org/10.1016/j.retrec.2025.101535
2. The data are available widely at the NREL website (www.NREL.gov) and the Oak Ridge National Laboratory (https://nhts.ornl.gov).

Data Format and Content

Charts and tables as well as the secondary databases after publication of our final report and journal papers will be made available on request to others not participating in this project. We would expect that upon completing their independent data analysis, researchers would cite our published work and/or provide co- authorship as necessary.

The usage of data not used towards publication will become a database to be used by other graduate students in GeoTrans.

Data Access and Sharing

We are working to develop a public database in which raw data may be deposited, we do not yet have infrastructure or funding to provide such a service but we can use the Open Source infrastructure Github. The most likely outcome is that we will provide unpublished data upon request, in exchange for authorship and/or establishment of a formal collaboration.

Reuse and Redistribution

There are no restrictions on the use of the data.

The UCSB team commits to follow the PSR Data Management Plan that is included in https://www.metrans.org/assets/upload/PSR_DMP.pdf .

Issued March 12, 2018 by METRANS Transportation Center, USC & CSULB. Below is a list of items that are relevant to this project.