Commercial Fleet Demand for Electric Vehicles in California: Current Fleet, Purchase Intentions, and Optimal Structure of Incentives

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In this project, the analysis of the commercial fleet demand for Battery Electric Vehicles (BEV) and Plugin-Hybrid Electric Vehicles (PHEVs) is approached in a *tripartite* way based on an overall conceptual framework developed within the project. Commercial fleets are vehicle fleets of large corporations, rental car companies, utilities, and government agencies. The data used here are the California Energy Commission (CEC) vehicle surveys of 2017 and 2019.The *first part* uses a mixed data cluster analysis to identify the demand dimensions of next vehicle replacement intentions by commercial fleet owners. We find segments of substantial demand size for PHEV and BEV in commercial fleets with PHEVs replacing smaller vehicles and expected to show higher efficiency and lower price than the overall average. BEVs are also replacing mostly smaller vehicles and expected to have almost double the efficiency of PHEVs and almost $20,000 higher price. The majority of fleet managers expect to replace current fleet vehicles with more efficient models of any fuel but at lower cost if they select internal combustion engine vehicles. We also find that managers attitudes and company current fleet characteristics are important determinants of the next vehicle procurement intentions. The *second part* identifies the specific vehicles that will be replaced by commercial fleets also using cluster analysis and multivariate analytical techniques. We find that ride hailing and delivery services may play an important role and there are systematic differences emerging from the type of use a car has in a fleet and its make/size but also fleet characteristics. The *third part* using choice experiment data identifies significant attributes underlying the choice of fleet managers in selecting new vehicles and related technologies that as expected include range, costs, and performance.

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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.

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Disclosure

Konstadinos G. Goulias and Hui Shi conducted this research titled, "Commercial Fleet Demand For Electric Vehicles in California: Current Fleet, Purchase Intentions, and Optimal Structure of Incentives" at the Department of Geography of University of California Santa Barbara. The research took place from 8/15/2022 to 8/14/2023 and was funded by a grant from the United State DOT/Pacific Southwest Region Transportation Center in the amount of $100,000. The research was conducted as part of the Pacific Southwest Region University Transportation Center research program.

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Abstract

In this project, the analysis of the commercial fleet demand for Battery Electric Vehicles (BEV) and Plugin-Hybrid Electric Vehicles (PHEVs) is approached in a *tripartite* way based on an overall conceptual framework developed within the project. Commercial fleets are vehicle fleets of large corporations, rental car companies, utilities, and government agencies. The data used here are the California Energy Commission (CEC) vehicle surveys of 2017 and 2019.The *first part* uses a mixed data cluster analysis to identify the demand dimensions of next vehicle replacement intentions by commercial fleet owners. We find segments of substantial demand size for PHEV and BEV in commercial fleets with PHEVs replacing smaller vehicles and expected to show higher efficiency and lower price than the overall average. BEVs are also replacing mostly smaller vehicles and expected to have almost double the efficiency of PHEVs and almost $20,000 higher price. The majority of fleet managers expect to replace current fleet vehicles with more efficient models of any fuel but at lower cost if they select internal combustion engine vehicles. The *second part* identifies the specific vehicles that will be replaced by commercial fleets also using cluster analysis and multivariate analytical techniques. We find that the most likely to be replaced vehicles are older small passenger cars with low efficiency. The *third part* using choice experiment data identifies significant attributes underlying the choice of fleet managers in selecting new vehicles and related technologies. We find as expected range, costs, and performance are important determinants of choice.

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Executive Summary

In the first part of the analysis in this project, Plugin Hybrid Electric Vehicle (PHEV) and Battery Electric Vehicle market segments were derived using cluster analysis on principal components. Then, cluster membership is analyzed based on desired/expected vehicle attributes by the respondents and compared to the overall sample responses. The two segments of interest here are the predominantly PHEV and BEV segments. The PHEV segment (204 from the 1712 respondents) contains 43.5% of the total responses preferring a PHEV to replace a current vehicle in the fleet, it is a segment that is composed of 100% PHEV preferring respondents and 99.51% of them expect to purchase a small vehicle within 5 years. The average price they expect to pay is approximately $27,000 and the expected efficiency to be about 55 Miles per Gallon equivalent (MPGe). The BEV segment (217 from the 1712 respondents) contains 99.50% of the BEV preferring respondents who are only 11.6% of the 1712. This segment also prefers small vehicles to replace vehicles in their fleet, possibly leasing and expecting to pay approximately $46,800 with an efficiency of about 100 MPGe. The other four segments are dominated by gasoline, diesel, and natural gas internal combustion engine vehicles and all of lower vehicle price than the overall average which is approximately $31,600. We also find that construction firms are less likely to opt for PHEV or BEV and health firms show the opposite, but their membership is spread in multiple market segments. Firms with investment in EV facilities and high preference for fuel efficiency are more likely to be the PHEV and BEV segments. In the regression that considers managers' attitudes are important determinants of purchase intentions. Cluster analysis to identify segments here shows a substantial demand size for PHEV and BEV in commercial fleets with PHEVs replacing smaller vehicles and expected to show higher efficiency and lower price than the overall average. BEVs are also replacing mostly smaller vehicles and expected to have almost double the efficiency of PHEVs and almost $20,000 higher price. The majority of fleet managers expect to replace current fleet vehicles with more efficient models of any fuel but at lower cost if they select internal combustion engine vehicles.

The second analysis in this report uses data collected on 5320 randomly selected vehicles from 2301 recruited commercial fleets for which specific questions about substitution were asked by pinpointing vehicles considered in each fleet. We first develop groups of vehicles that have similar replacement propensity using cluster analysis on mixed data to classify vehicles in groups of no replacement by electric cars, replacement by a combination of electric cars and contract services, and replacement by electric cars but not contract services. Then we analyze the vehicles that will be replaced to identify characteristics making them suitable for each of the three types of replacement. The analysis here shows first that the majority of fleet vehicles can be replaced by electric vehicles. We also find diversity in vehicle replacement

propensity that is a function of vehicle age, size, and type of utilization of the vehicle to be replaced. We also find differences based on fleet size and the type of business of the owner firm of the fleet.

This analysis shows that contract and ride hailing services can be a major competitor of ICE vehicles in fleets. This aspect has been neglected in the EV literature and in this paper we show both competition with PHEV and BEVs but also complementarity. The questions here that included vehicle fuel, type/size, but also current use and the possibility of replacement of these current fleet vehicles and their substitution by other types of vehicles as well as contract services enables this type of analysis providing evidence of the continuum of complementarity of uses as portfolios of services but also replacement of older vehicles and less efficient vehicles. Contract services can function as substitutes of fleet vehicle purchase and may be viewed as services provided by transportation fleets to other industries. One limitation, however, is the absence of a substantial sample clearly identified as TNCs such as Uber, Lyft and total absence of couriers and express delivery services. In fact, TNCs are classified under "Transportation and Warehousing" with a small percentage in this sample and fleets of couriers and express delivery services (UPS, FedEx, DHL, etc) are entirely absent. This should be rectified in future surveys to explore the impact of recent trends among these services in favor of electric vehicles in basic and premium services [25] and the ongoing electrification of delivery service companies [26]. In any case, however, the findings here support a different type of public incentive than tax rebates. For example, governments could provide vouchers for the use of EV ride hailing and scrappage programs targeting specific vehicles in fleets with options to engage service contracts with delivery services that also use EVs.

The third analysis uses stated choice scenario data from 2017 and 2019 indicating companies are willing to spend approximately $58 more to increase vehicle range by one mile, $17.412 more to decrease annual maintenance costs by one dollar, roughly $294 more to increase MPG by one mile, $1,881 more to reduce acceleration time by one second, and $2,811 more to acquire a vehicle that is one year newer in 2017. The analysis in 2019 did not yield realistic estimates and testing of random variation is willingness to pay was not reliable. However, more analysis is needed beyond this report to test these findings further and using more sophisticated tools than used here.

1. Introduction

Vehicle technology changed dramatically in the past 20 years. Today, electrification in the form of Battery Electric Vehicles (BEV) and Plugin-Hybrid Electric Vehicles (PHEVs), together called PEVs herein, is emerging worldwide as a preferred technology in our transition away from fossil fuels (Zheng et al., 2020, Muratori et al., 2021). The IEA (2021) in its electric vehicle outlook reports 10 million PEVs worldwide with a 41% increase in 2020 registrations with China, Europe and the United States as the three leaders in PEV market penetration. This is repeated in the IEA Global outlook for 2022 with China continuing adding EVs in its national fleet faster than other countries but also the US and Europe accelerating they transformation of national fleets away from internal combustion engine (ICE) cars. This is attributed to a combination of incentives backed by sustained policy support, pledges to phase out internal combustion engines and setting targets for EV market penetration, increasingly stricter emissions standards and energy efficiency , and increased variety of model production by automotive industry attracting wider market segments of buyers. As of December 2020, the United States has over 276 million registered vehicles nationwide of which approximately 30 million are in California (US Department of Transportation, 2022). Approximately 1 million of the nationwide fleet of vehicles are electric of which 425,300 are registered in California (US Department of Energy, 2022).

California not only has been at the forefront of electromobility but is also showing faster rising of sales than any other state (https://evadoption.com/ev-market-share/ev-market-share-state/). This is further strengthened by California's latest proposed legislation dubbed "California Blueprint" that according to mass media includes "*$3.9 billion for the electrification of ports, heavy-duty trucks, school and public transit buses in the state, $1.2 billion on 40,000 passenger electric vehicles and 100,000 new charging stations in California by the end of 2023 and $1 billion on other zero emission vehicle initiatives."* (CNBC, 2022). With increasing market penetration of PEVs, battery charging infrastructure deployment that provides cheaper and more convenient charging options becomes a priority and the California Energy Commission's investment of $100 million for the Clean Transportation Program is setting the background for acceleration in infrastructure development and deployment as well as provision of incentives for vehicle purchase. Commercial fleets can play a major role in this rapid evolution not only for the transportation system but also for an envisioned integrated system of energy production and consumption called "smart grid." However, the demand for PEVs by commercial fleets has received scant attention in research.

Commercial fleets are vehicle fleets of large corporations, rental car companies, utilities, government agencies, and smaller operators providing services to businesses and dwellings. Depending on the definition of the commercial sector and the inclusion of small and large companies, current estimates show a nationwide commercial fleet of a little over 8 million vehicles that is approximately 3% of the total US vehicle fleet (US DOT, 2022). If a similar ratio applies to California, commercial fleets may be close to 1 million vehicles in California. Considering that fleet renewal and adoption of PEVs is part of a more complex planning cycle, it is worth digging deeper into ways to increase PEV market penetration and customize incentives to different fleets (Baykasoğlu et al., 2019). In fact, in countries like Germany the majority of new passenger cars are purchased by companies and agencies for their employees to share and these same companies are replacing their older cars with new models (Globisch et al., 2018). This is a particularly attractive feature of commercial fleets because they function as agents of change and they may develop a used car market offering lower cost EVs to consumers who according to the specialistic literature find current new models expensive even under generous governmental purchase-based and use-based incentives (Kumar and Alok, 2020). These are well documented advantages of using fleets as agents of change in vehicle technology in the market and on top of that due to their operations have a higher potential in emissions reduction, easier to charge and/or refuel in headquarters, and targeting fleets with high turnover rates may be an administratively efficient way to achieve market penetration of new technologies because a small number of fleets control a large percentage of cars (Nesbitt and Sperling, 2001).

1.1 Data Used in this Project

This research uses data from the 2017 California Vehicle Survey (CVS), which is one of the set of surveys conducted by the California Energy Commission on residential and commercial light-duty vehicle ownership (NREL, 2023). The survey has taken place periodically over the past two decades to update light-duty vehicle ownership and preferences and forecast the shift in utilization behavior. To the best of author's knowledge, the 2013, 2017 and 2019 CVS are the first datasets of public agency surveys (available to the public and used for decision making about car ownership and type policies) that collect information on commercial fleet *attitudes, perceptions, and values* towards PEVs in California. These surveys contain two separate vehicle owners that are the private vehicle owners that are households living in California and named the residents (and residential fleets) and commercial fleet owners that are single or multiple establishment firms in California and named commercial fleets. Data collection for both residential and commercial subjects follow a two-stage approach in which the first stage is a questionnaire that collects current fleet data, a variety of attitudinal data that change with the survey year, and intentions data about the next vehicle and/or what people do with any discarded vehicles. In the second stage hypothetical choice scenarios customized to each respondent collect data mimicking real life choices people make (Hess et al., 2009, 2012).

We first explore the intentions fleet managers have to purchase or lease vehicles when they go through renewal of their fleet decisions. This includes the **decision to purchase or lease a car, adding or replacing a fleet car, vehicle size, vehicle fuel type, efficiency and price of the next car.** To do this analysis we extract from the data market segments with distinguishable characteristics based on the variables above. The battery electric vehicle market segments are different from the plugin hybrid electric vehicles. They are also very different from their counterparts internal combustion engine market segments.

In a second analysis using data from 2019, we also pinpoint the vehicles that will be replaced and identify the potential for them to be replaced by electric cars or to be replaced by outsourcing services such as ride hailing for passengers and ride hailing for delivery of goods.

In both analyses we use as determinants of the decisions the current fleet composition, firm/agency characteristics such as size and type of industry, as well as preferences about specific vehicle attributes. When we target specific vehicles for replacement we also use vehicle age, size, fuel used, annual miles, and type of utilization of the vehicle to be replaced. The analysis includes data from the California Vehicle Survey conducted by the California Energy Commission (CEC) in 2017 and 2019.

In the final analysis in this report we explore willingness to pay for a variety of attributes by commercial fleets using Random Utility Models (RUM) and discrete choice model estimation.

1.2 Brief Literature Review

The research literature on PEV market penetration is rich and has now shown that car attributes such as the driving range of a car with one battery charge, the spatial distribution and availability of charging stations, the cost of initial purchase, and social influence are major decision factors in PEV purchase (Liao et al., 2017, Chakraborty et al., 2022). However, the efficacy of PEV-specific taxation credits and other incentives provision for the purchase of PEVs is unclear (Coffman et al., 2017). Moreover, private owners (i.e., households) may also exhibit a high risk of discontinuance that is defined by Hardman and Tal (2021) as "*abandoning a new technology after first purchasing it* [PEVs]." In that research they find discontinuance happens in approximately 20% of their survey participants in California. This is attributed to lower household car ownership levels, owning less efficient vehicles, and lack of availability of fast charging and other charging opportunities. Some of these concerns may be minimized when major infrastructure deployment happens. In parallel, the PEV technology is evolving in a way that provides differentiated amenities among different types of vehicles and does not target only the residential private vehicle owning public and includes private and public commercial fleets (Sanguesa et al., 2021). In an ideal future we need to overcome large-scale diffusion of technology barriers (Lebrouhi et al., 2021) and deploy PEVs in an integrated system that includes a smart electricity grid combined with photovoltaic power production (Fachrizal, 2020). Experiments with this coupling of privately owned vehicles with a smart grid illustrate the difficulties and possible solutions requiring further study (Alizadeh et al., 2017, Morapidari and Alizadeh, 2019). As we see below the ideal PEV owner-partner, however, in this type of integrated system may not be a large commercial fleet. Instead, a group of smaller fleets that are spatially dispersed can be used in an optimally managed system. The high potential of PEV fleets in this context is mainly due to the central management of fleets that can be optimized to decrease the mismatch of demand and infrastructure capacity (to avoid underutilized charging stations) and minimize the mismatch of demand and supply in the power grid (e.g., to avoid electricity price spikes, voltage instability, and feeder capacity violations). Commercial fleet operators can alleviate and manage centrally some of these issues (Kettles, 2016). Moreover, through their commercial fleet renewal supply of vehicles in the used vehicle market will increase and this will increase PEV affordability for consumers (Oliveira et al., 2017, Tal et al., 2021).

The most recent research (Bae et al., 2022, Sugihara and Hardman, 2022) on commercial fleet decision makers of heavy-duty vehicles (HDV) and light duty vehicles (LDV) we find that many fleets have many similar motivations and inhibiting factors to adopt PEVs with households but also show fleet specific factors impacting decision making in purchasing and using PEVs. In both residential and commercial market segments vehicle costs and performance, infrastructure availability, purchase and use incentives, and social support are important considerations either as direct influencers of the purchasing decisions or through attitude/perception mediation (see the reviews and metanalysis in Giansoldati et al., 2017; the review in Coffman et al., 2017; and the reviews on commercial fleets in Rosenberger et al., 2022, and Bae et al., 2022). Commercial fleets have some additional supporting aspects and barriers for the adoption of PEVs and these include characteristics and composition of the current fleet, functional compatibility with the company's work, ease of use, fuel technology, longer vehicle range and availability of supporting infrastructure, cost savings computed in terms of total cost, environmental benefits, higher up-front costs, uncertainty about ongoing costs, safety and reliability of the technology, image of the company, economies of scale in maintenance, and perceptions and attitudes of fleet purchasing agents and users (vehicle drivers/operators). These are just a few aspects that are found also among fleet managers in other countries too (Gnann et al. 2013, 2015, Globisch et al., 2018a, 2018b). However, there are key differentiating functional requirements and contexts that need further investigation (Jones et al. 2020, Mohammed et al., 2020, Di Foggia, 2021) and country-specific institutional settings and barriers or enablers (Khan et al., 2021, Skowrońska-Szmer and Kowalska-Pyzalska, 2021, and Roemer and Henseler, 2022).

When exploring the correlation among all these influences we need to identify specific aspects and their role played in the vehicle procurement decision making and their strength in explaining commercial fleet vehicle electric vehicle adoption. Below we teased out of the literature influences on the propensity of commercial fleets to switch their behavior away from the traditional ICE cars burning gasoline, diesel, or compressed natural gas (CNG). Analysis of this dates back when alternative fueled vehicles were just starting to appear on the market (Golob et al., 1991, and 1995). The attributes considered by fleet managers 30 years ago have many similarities to more recent data analysis of the propensity to replace a car in the current fleet and/or purchase an electric car (either hybrid or battery electric car). Table 1.2.1 shows a selection of studies, the type of data collection, sample size, and a list of variables found to be significant determinants and/or important mediators for these decisions together with a brief summary of findings. Rosenberger et al., 2022, provide a review of the methods used to assess electric mobility with particular attention to commercial fleets and classifies the studies into *total cost and life cycle analyses*, *optimization models*, *choice models*, and *other applications* that include reviews and in-depth studies. In this report we are interested in identifying behavioral relationships to guide our analytical specifications and we exclude from the review here normative (aka fleet optimization) studies and studies that address narrowly defined issues such as exclusively charging behavior and the study of single factor influence. Instead, we include studies that explored empirically cause and effect relationships between fundamental determinants such as fuel costs and fleet characteristics. However, we also search for information to help us in the task defined earlier to understand a more complete array of decisions such as *purchase new vs used car*, *lease vs buy a car*, *adding to the fleet vs replacing a fleet vehicle*, *body size of the vehicle*, *fuel type of the vehicle* (with more attention to electricity), *energy efficiency* (aka miles per gallon equivalent), and *purchase price*. The selection of these aspects is motivated by a need to specify a comprehensive demand model for fleet vehicles moderated by the data we have available.

The list of the reviewed studies below is chronological and includes other alternatives to fossil fuels in addition to electricity but focusing on commercial fleets. One of the early studies identifying the considerations of fleet managers when deciding to adopt and purchase electric vehicles is by Berg, 1985. Table 1.2.1 provides a summary of the determinants considered to be important driving this decision and they are at the level of the vehicle (cost and performance), the fleet and vehicle utilization, surrounding infrastructure, and an array of attitudes and perceptions about the vehicle technology and supporting environment towards the technology. In a subsequent study (Golob et al. 1995; Golob et al. 1997), describe a survey of approximately 2000 fleet sites that were contacted first in a computer aided telephone interview followed by a mail survey about vehicles in the fleet and then subjected to a choice experiment manipulating vehicle attributes (the authors call this a stated preference survey but later the specialistic literature settled for the label discrete choice experiment), and a survey component about attitudes, intentions, and fleet decision making characteristics. In the Golob et al.(1995, 1997) analyses many of the Berg et al., 1985 vehicle and fleet attributes were tested in a conditional logit model applied to hypothetical scenarios and Table 1.2.1 shows the attributes that were found to be significant determinants of the choice of alternative fuels in the model estimation. The choices that are analyzed are based on hypothetical scenarios designed by changing values of vehicle attributes in combinations offered to survey respondents who are asked to select one out of four options. In a subsequent study, Stinson et al. (2020) in the context of estimating the fleet composition of business establishments to develop a freight travel forecasting simulator, identified in a nested logit model and a factor analysis as important characteristics for purchasing light duty vehicles (LDV) PEVs by commercial fleets attributes such as seating capacity, hauling capacity, vehicle body type, cost, range for PEVs, battery life for PEVs, lack of supporting infrastructure, and lack of familiarity with PEVs.

Frenzel et al., 2021, is another study that provides information about a similar array of potential determinants in the decision making about electric vehicles in fleets using a qualitative research method in which text analysis was used. They find that different early adoption of different fuels applies to trucking and logistics in larger fleets and they are better aligned with renewable fuels. They also conclude late adoption is most likely to happen in smaller firms. They also find secondary influences such as environmental considerations and confirm that decisions about electrification are strongly correlated with decisions about other renewable and non-renewable fuels. The final study in Table 1.2.1 by Khan et al. (2021) reports on findings from a Canadian stated choice survey experiment (with revealed choice questions about the current fleet and attitudes) of more than 1000 commercial fleet respondents segmented into four distinct groups based on the attitudes and perceptions about EVs and they find similar vehicle attributes explaining choices among the hypothetical scenarios of costs and technology performance as in the rest of literature but they also find substantial heterogeneity across each group identified using latent class clustering (Table 1.2.1 provides additional details). In summary, from this literature review we identify “blocks” of determinants in the decision making of car ownership change decisions in commercial fleets that are:

- *Decision making styles* (Nesbit and Sperling, 2001, Skippon and Chappell, 2019, Bae et al., 2022). This includes vehicle procurement processes and roles played by decisions makers, bundling of vehicle characteristics and relative weight assigned to each attribute (e.g., purchase and operating cost, energy efficiency, emissions), firm-dependent assessment of the charging environment, and sustainability plans within the specific business.
- *Current fleet characteristics and vehicle use* (Table 1.2.1 and Bae et al., 2022). This includes fleet size, mix of different fuels and vehicle types, mix of different daily uses of vehicles in the fleet, facilities for maintenance and refueling/recharging, location of refueling/recharging (e.g., employees homes, within a radius around the fleet yard), allowance to use fleet for personal purposes, knowledge and technical staff to perform maintenance tasks. Also, industry type of the business using the fleet, daily uses of the fleet vehicles (e.g., distances travelled, stops made, fixed vs flexible routing) are also important.
- *Managerial and driver attitudes/concerns* (Table 1.2.1, Sierzchula, 2014, and Bae et al., 2022). Concerns, perceptions, knowledge, and familiarity with the technology (e.g., costs, reliability, service availability, long term sustained support by institutions), willingness to innovate and protect the environment, risk taking, image creation for the firm, government or private grants.
- *Technology and vehicle under consideration* (Table 1.2.1, Golob et al., 1991, Brown, 2022, Bae et al., 2022, Romjue, 2021). Fit for the purpose/use, costs and energy efficiency, capabilities (e.g., towing and range), infrastructure, environmental impacts, variety of purchase and lease options, technology availability and manufacturer maintenance and assurances.
- *External determinants/influences* (Table 1.2.1, Li et al., 2016, Biresselioglu et al., 2018, Bae et al, 2022, Romjue, 2021, Brown, 2022). Financial incentives for vehicle and infrastructure, earmarking grants by local and state agencies (e.g., counties, California Energy Commission), local regulations

and policies on vehicle use restrictions, State and Federal regulations and vehicle standards on emissions (e.g., zero emitting vehicle standards) and energy efficiency (e.g., Corporate Average Fuel Efficiency standards), and perception of policies.

In the next sections we first identify groups of commercial vehicle fleets that have commonalities in terms of the vehicle intended transactions in procuring their next vehicle. Then, we study their composition and correlation with other contextual factors the literature review above found as significant determinants of this behavior.

Table 1.2.1 Determinants of commercial fleet car ownership decisions

Source	Data	Methods/ Models	Exogenous Variables & Mediators	Findings and Notes
Berg, 1985	583 fleet manager interviews on electric vehicles in 1983 in United States.	Descriptive analyses of interview data and cross tabulations & bar charts	Vehicle/battery range, top speed, acceleration, purchase cost, operating cost, maintenance cost, fossil fuel cost, electricity cost, availability of repair and parts, daily use of vehicles in miles per day and route fixity, frequency of stops and starts, duration and location of parking vehicles, vehicle size, charging availability, purpose in vehicle use. Industry type of the fleet, fleet size, flexibility of use/substitution in use, trucks in the fleet and truck payload, US region. Attitudes and perceptions about protection from fuel price shocks, operational characteristics, vehicle performance including range and speed, availability of charging infrastructure, battery life, and organizational and individual resistance to change.	Prediction of size and characteristics of potential market for EVs for light duty vehicles (< 5,000 lb). Estimated to be between 2.5 million to 7 million vehicles. High EV substitution potential for light-duty pickup trucks and vans, large fleets, and in the Northeast and Northcentral United States.
Golob et al. 1997 & Golob et al., 1995	2023 surveys from fleets of 10 or more vehicles in a 1994 California survey about alternative fueled vehicles (electricity, compressed natural gas, or methanol) – many stages see text.	Regression of VMT on fleet characteristics, Probit model for awareness of legislative mandates, and conditional logit model applied to hypothetical scenarios of combinations of costs and fueling characteristics.	In the choice model estimated: Vehicle/battery range, purchase cost, peak and off-peak fuel cost, operating cost (maintenance cost, fossil fuel cost, electricity cost), availability of repair and parts, cargo capacity, emissions, vehicle size, on-site charging availability and duration, purpose in vehicle use Industry type of the fleet and fleet size.	Unclear size of the commercial fleet market but estimated to be 20 times smaller than the residential market. Heterogeneity in purchase cost sensitivity depending on the industry type. Heterogeneity in the range and utilization category sensitivity. Heterogeneity in the type of fuel (electricity vs NGV vs MV)

Table 1.2.1 Determinants of commercial fleet car ownership decisions (continued)

Stinson et al. 2020	CEC California Vehicle Survey data of 2017 from 1693 fleet interviews on intentions for next vehicle in the fleet	Nested logit model for fuel choice and factor analysis of respondent attitudes & concerns.	Seating capacity, hauling capacity, vehicle body type, cost, range for PEVs, battery life for PEVs, lack of supporting infrastructure, and lack of familiarity with PEVs.	Heterogeneity of decision sensitivity based on fleet size and industry type.
Frenzel et al., 2021	Group discussions in 4-hour sessions preceded by background questionnaires in 2019 in Berlin/ Brandenburg Metropolitan Area	Mayring content analysis of text from the sessions on use of renewable fuels, drivers and barriers, comparisons to alternative vehicles, and industry aspects of acceptance	Costs in general and fuel costs in particular. Daily use of vehicles such as route planning, versatility, usage preferences. Consideration of lifecycle environmental impacts. Taxation and regulations, phased implementation with incentives first and profitability/savings second, vehicle technology readiness, comparative advantages among different fuel options, knowledge about options, and knowledge about the policy change horizons. Supporting infrastructure, driving range, minimum detours to refuel, fuel availability. Corporate image.	Identified early and late adopters of new fuels and electricity. Heterogeneity in adoption propensity among different companies/fleets. Large logistics and transportation companies early adopters. Scrappage policies found not as an effective strategy to replace older vehicles.
Khan et al., 2021	Revealed and Stated Choice Experiment with 1008 fleet organizations In 2016 in Canada	Latent Class Multinomial Logit (MNL). The latent classes depend on the responding person's attitudes and perceptions and the utility of the MNL on vehicle choice attributes	Utility attributes found significant in the MNL are: purchase price, annual operating cost, range per recharge, charging time, public charging within a 5 km buffer, type of fleet, type of organization and technical capabilities and charging locations, perception of risk. Latent class membership with the classes ordered in terms of EV orientation was found to depend on size of the organization, attitudes/perceptions about energy independence of Canada, cost-effectiveness, willingness to invest, image, technical capabilities, risk, industry pressure/influence, willingness to invest in infrastructure.	Identified a hierarchy of groups in orientation to EVs adoption and different sensitivity to vehicle technology costs and characteristics for each of the groups.

2. Commercial Fleet Market Segments

2.1 Data Used in the First Analysis

This research uses data from the 2017 California Vehicle Survey (CVS), which is one of the set of surveys conducted by the California Energy Commission on residential and commercial light-duty vehicle ownership (NREL, 2023). The survey has taken place periodically over the past two decades to update light-duty vehicle ownership and preferences and forecast the shift in utilization behavior. To the best of our knowledge, the 2013, 2017 and 2019 CVS are the first datasets of public agency surveys (available to the public and used for decision making about car ownership and type policies) that collect information on household and commercial fleet *attitudes, perceptions, and values* towards PEVs in California. These surveys contain two separate vehicle owners that are the private vehicle owners that are households living in California and named the residents (and residential fleets) and commercial fleet owners that are single or multiple establishment firms in California and named commercial fleets. Data collection for both residential and commercial subjects follow a two-stage approach in which the first stage is a questionnaire that collects current fleet data, a variety of attitudinal data that change with the survey year, and intentions data about the next vehicle and/or what people do with any discarded vehicles. In the second stage hypothetical choice scenarios customized to each respondent collect data mimicking real life choices people make (Hess et al., 2009, 2012).

Table 2.1.1 shows a selection of variables characterizing the 1712 participant fleets in the survey. This shows variation in the types and sizes of the recruited fleet and we will use in the analysis here to identify if these characteristics are significantly associated with the type of vehicle that will be procured by each of these fleets next. Table 2.1.2 shows the answers to the question: "When selecting a vehicle for your business, what do you consider to be the top 3 attributes? (Select up to 3)." This gives us the opportunity to test if this stated importance of vehicle attributes correlates with the intention and type of the next vehicle to procure for the fleet.

Table 2.1.1 Company and Fleet Characteristics

Characteristic	**N = 1,712**[1]
Number of Workers	39.81 (640.97) [3.00] (25,000.00)
Number of Light Duty Vehicles	4.33 (26.35) [2.00] (800.00)
Number of Gasoline Vehicles	2.99 (15.74) [1.00] (500.00)
Number of Gasoline Vehicles	0.58 (7.91) [0.00] (300.00)
Fleet has Solar Panels	268 / 1,712 (16%)
Fleet has Volt240Chargers	149 / 1,712 (8.7%)
Fleet has No Refueling	1,288 / 1,712 (75%)
Company has Charging Equipment	139 / 1,712 (8.1%)
Construction Company	163 / 1,712 (9.5%)
Retail Company	172 / 1,712 (10%)
Real Estate Company	133 / 1,712 (7.8%)
Professional Company	378 / 1,712 (22%)
Health Company	112 / 1,712 (6.5%)
Other Company	195 / 1,712 (11%)

[1]Mean (SD) [Median] (Maximum); n / N (%)

Table 2.1.2 Percentage of the Top Three Considered Attributes
(Answer to the question When selecting a vehicle for your business, what do you consider to be the top 3 attributes? (Select up to 3))

Characteristic	**N = 1,712**[1]
Vehicle Price	1,199 / 1,712 (70%)
MPG	899 / 1,712 (53%)
Acceleration	57 / 1,712 (3.3%)
Maintenance Cost	493 / 1,712 (29%)
Fuel Cost	157 / 1,712 (9.2%)
Range	160 / 1,712 (9.3%)
Towing Capacity	144 / 1,712 (8.4%)
Cargo Capacity	448 / 1,712 (26%)
Seating Capacity	200 / 1,712 (12%)
Reliability	696 / 1,712 (41%)
Fuel Availability	63 / 1,712 (3.7%)
Refueling Time	18 / 1,712 (1.1%)
Horsepower	54 / 1,712 (3.2%)
Warranty	95 / 1,712 (5.5%)
Brand/Vehicle Make	349 / 1,712 (20%)

[1]n / N (%)

2.2 Market Segments Based on Commercial Fleet Intentions

The 2017 survey (herein labeled CEC2017) has a set of questions specifically designed to collect information about the next vehicle procurement, therefore, it is used in this study. CEC2017 also contains questions to fleet managers about the size and composition of the current fleet, desired attributes of the next vehicle to be added to the current fleet (either as addition or replacement of a previously purchased or leased vehicle), and a series of choice experiments to contrast vehicle attributes. In this paper using the CEC2017 data we explore the purchase intentions and the relationships between the next vehicle and the current fleet using a technique that combines categorical with continuous vehicle attribute data as explained later. The questions from 1712 participants (commercial fleet owners) in CEC2017 survey that we analyze jointly to derive market segments are:

- When do you think you may purchase or lease one or more light-duty vehicles that will be company-owned/leased and/or used for business purposes in California at least 50% of the time? This was recoded as <= 5years and > 5years
- Will the next vehicle your company plans on acquiring most likely be new or used?
- Will the next vehicle your company plans on acquiring most likely be purchased or leased?
- Will the next vehicle your company plans on acquiring be an addition to your fleet or a replacement?
- What type of vehicle is your company most likely to purchase or lease next? This answer is one of 13 options from a subcompact car to a full-size large van.
- What type of engine/fuel type is the next vehicle your company acquires most likely to have? This answer is one of Gasoline, Hybrid (Gasoline), Plug-in Hybrid Electric vehicle (PHEV), Gasoline-ethanol Flex Fuel vehicle (E85 FFV), Diesel, Compressed Natural Gas (CNG) vehicle, Full Electric Vehicle, and Hydrogen vehicle.
- About how many miles per gallon (MPG or MPGe) do you expect your company's next vehicle to get, on average? (city/highway combined average)
- About how much money do you expect the company will spend to purchase/lease its next vehicle?

These are six categorical variables and two continuous variables that we will use to derive market segments of commercial fleets. Table 2.2.1 provides a summary of the statistics of this sample.

Table 2.2.1 Variables Used in Developing Market Segments

Characteristic	N = 1,712[1]
Purchase Or Lease	
Purchase New	784 / 1,712 (46%)
Purchase Used	564 / 1,712 (33%)
Lease	364 / 1,712 (21%)
Add Or Replace	
Add	286 / 1,712 (17%)
Replace	1,426 / 1,712 (83%)
Soon Or Later	
Buying in <= 5yrs	1,326 / 1,712 (77%)
Buying in > 5yrs	386 / 1,712 (23%)
Fuel Type	
Electric or Hydrogen	199 / 1,712 (12%)
PHEV	469 / 1,712 (27%)
ICE (gasoline or other)	1,044 / 1,712 (61%)
Vehicle Size	
Small	725 / 1,712 (42%)
Medium	457 / 1,712 (27%)
Large	530 / 1,712 (31%)
Price	31,663.4 [30,000.0] (22,236.8)
MPGe	38.6 [25.0] (34.5)
[1] n / N (%); Mean [Median] (SD)	

2.3 Market Segment Derivation

The preferred method to identify determinants of the demand for vehicles in traditional car ownership and use analyses is a Random Utility Model (RUM) that can provide the probability to select a specific vehicle type. The type can be a combination of body type (e.g., compact car, sport utility vehicle, pickup truck) and fuel type (e.g., gasoline, diesel, BEV, PHEV and so forth). Some model formulations aim at examining vehicle holdings and how different types of vehicles are used using RUM-based fleet allocation to annual vehicle miles and to the specific persons who are the primary drivers such as the Multiple Discrete Continuous Extreme Value models (Paleti et al., 2013, Vyas et al., 2012). Other formulations estimate the probability for specific types of vehicles to be procured by decisions makers (mostly by households in the transportation literature) that have also included the transaction portion of replacing an older vehicle or adding a vehicle to the fleet (Brownstone et al., 1996, Paleti et al.,2011). More recent applications using different databases are also estimating models that correlate choices with attitudes (Iogansen et al 2023). The survey data we use here was collected to create and update the CEC vehicle fleet evolution and yearly forecasts of market penetration of zero emitting vehicles and greenhouse gas emissions for California (CEC, 2018, Ledna et al., 2022). All these past analyses have in common assumptions about the behavioral mechanism (e.g., consideration of all possible options in RUM) used by decision makers when they face the possibility of replacing an older vehicle or adding a new vehicle to their fleets. They also make restrictive assumptions about the unobserved variation of these decision makers (e.g., the extreme value distribution followed by this randomness that in turn allows to formulate Logit and Logit-like regression models). Moreover, the analysis in the past is limited to a couple of behavioral facets (replacement of a current vehicle and type of vehicle to replace it). In the analysis here we opt for a group of methods that enables derivation of market segments using all the information highlighted in the data section but with the minimum possible number of assumptions about the data generation process. So, we are combining multiple facets of the decision to procure a vehicle for a fleet (e.g., size and type, price and efficiency, timing, and purchase or lease). This is by far more comprehensive than other modeling attempts in the literature.

The method used here belongs in the cluster analysis family of methods that aim to divide observations into groups according to variable values these groups have in common. The ultimate objective is to partition the data in such a way that commercial fleet respondents in the same group are similar (e.g., plan their next vehicle in the fleet to be a large car with internal combustion engine that costs about $30K and does on average 25 miles to the gallon) but at the same time dissimilar from other groups (e.g., one group that seeks to buy a small PHEV that costs about $25K and does on average 100 miles to the equivalent gallon). It is usual to differentiate between methods that are algorithmic, and they discern patterns in multidimensional data clouds (these are also labeled unsupervised methods) from methods that are model-based and require assumptions about the data generating distributions.

The algorithmic approaches are the earliest clustering techniques and include the well-known K-means, K-medoids, Hierarchical clustering among many others (Kaufman & Rousseeuw, 2009). Early concerns about important questions on deciding about the right number of clusters, treatment of outliers, and uncertainty about the right partition motivated the second family of methods that specify a probability model for the data (e.g., the likelihood function). To fill this void model-based cluster methods were developed that make assumptions about the probability distributions of the data analyzed (in reality a mixture of these distributions as in Vermunt and Magidson, 2002) and evolved into a major field of data analysis that span the entire taxonomy of data types from simple continuous variables to text (Bouveyron et al., 2019). One of the thorniest problems in model-based clustering, however, is the specification of joint distributions of data that are fundamentally different such as binary variables with multicategory variables, censored and truncated variables, and continuous variables with restrictive assumptions needed to write the likelihood function that will be used to estimate model parameters (Nylund-Gibson and Choi, 2018, Weller et al., 2020). To avoid imposing restrictive assumptions on our data we opted here for a model-free algorithmic method in creating clusters and took advantage of more recent developments in data analysis of mixed types of variables (discrete and continuous) and a variety of diagnostics about cluster quality.

The method we use here is a distance-based clustering of mixed data (van de Velden et al., 2019). The word "mixed" refers to quantitative (in our case continuous data such as MPGe and vehicle price) and qualitative (in our case categorical that are either binary as the yes/no answer to purchasing a vehicle or multicategory as in the fuel used by a prospective vehicle). Cluster analysis in this approach is the second step after a data combination and reduction step called Factor Analysis with Mixed Data (FAMD). The data are viewed as a table of rows representing the individuals and columns representing the variables with the continuous variables standardized (subtract their mean and divide by their standard deviation) and the categorical variables transformed into dummy variables and divided by the squared root of the category proportion. This decreases the possibility that one variable "dominates" all the other variables due to its size or due to each frequency of choice.

The resulting matrix of rows of individuals and columns of the transformed variables is then used to derive principal components projecting the observed data on an orthogonal coordinate system (axes that yield uncorrelated components) that captures variation in the data in a hierarchical way with the first component having the highest variation, the next component having the second highest variation and so forth until 100% of the observed variation is represented in the new coordinate system. This allows to identify components that map the entire variation in the data from all the variables jointly. Then, retain for the subsequent cluster analysis the desired number of components based for example on the percent of variance that is considered the signal (the variation we want to explore further) versus noise in the data.

FAMD in the way that is presented in Pagès (2004), Husson et al. (2017), and implemented in FactoMineR (Lê et al., 2008) uses the matrix of the transformed variables described before. This is equivalent with the use of a pairwise distance (dissimilarity) between observations as the Euclidean distances used in Principal Component Analysis (PCA) for the continuous variables plus the sum of the chi-square distance contributions used in Multiple Correspondence Analysis (MCA) for the categorical variables (Pagès, 2004, van de Velden et al., 2019). This technique produces principal components representing dimensions of the desired vehicle characteristics (price, efficiency, size and fuel type, timing of vehicle procurement, replacement of current vehicle or addition to the fleet, and intended purchase of new, used, or lease). These are the variables presented in Table 2.2.1 above.

In the FAMD application here (the first step) after the derivation of the new coordinate system (the principal components) we retain 8 principal components capturing approximately 91.55% of the variance in the variables listed above. Table 2.3.1 shows the 8 principal components and the amount of variance captured by each component.

Table 2.3.1 Principal Components and Variance Captured in the Projection

Components/ Dimensions	eigenvalue	Variance Percent	Cumulative Variance Percent
1	2.26	22.62	22.62
2	1.39	13.91	36.53
3	1.17	11.69	48.22
4	1.10	11.01	59.24
5	0.96	9.57	68.81
6	0.86	8.61	77.42
7	0.77	7.74	85.16
8	0.64	6.39	91.55

Then, these 8 principal components are used in a hierarchical clustering routine to extract market segments (clusters) with systematic differences and similarities in their principal components and by reflection of the projection on the principal components of the original variables. Before presenting the findings it is worth mentioning that deciding on the number of clusters to retain in analyses of our type cannot be done exclusively based on indicators of “good” clusters. For example, one popular indicator is the total within cluster sum of squares. This tells us that we minimize the amount of variation of the behavioral/attitudinal variables within each cluster by increasing the number of clusters. There are many types of indicators (statistical criteria) one can use to identify the “optimal” number of clusters and they are available in an R library (Charrad et al., 2014).

As in most clustering methods to partition the observations here we aim to find groups (classes) with small within-class variability and large between-class variability. When we work with inertia we can achieve both aims contemporaneously because total inertia (which is a constant for the data we have) is the sum of within-class inertia and between-class inertia as shown in Equation 2.3.1.

$$\sum_{k=1}^{K}\sum_{q=1}^{Q}\sum_{i=1}^{N}(x_{iqk}-\overline{x}_k)^2=\sum_{k=1}^{K}\sum_{q=1}^{Q}\sum_{i=1}^{N}(x_{iqk}-\overline{x}_{qk})^2+\sum_{k=1}^{K}\sum_{q=1}^{Q}(\overline{x}_{qk}-\overline{x}_k)^2\ [Equation\ 2.3.1]$$

i= 1,…,N observations

q = 1,…,Q classes

k= 1,…,K variables

x_{iqk}= value of variable k in class q for individual i

$\overline{x}_k$= value of overall average for variable k

$\overline{x}_{qk}$= value of average for variable k within class q

Hierarchical clustering when it is agglomerative starts will all the observations in one cluster (one class). This means the between inertia is equal to the total inertia. Then at a sequence of steps observations first and clusters afterward are combined to minimize the decrease in between-class inertia. In this way, observations are classed in the same cluster by minimizing the decrease in the between-class inertia. The difference between two cluster steps (one step with q and the next with q+1) is computed and if appearing to be a large difference the q+1 number of clusters solution is accepted. This is shown in Figure 2.3.1 left-hand side with an abrupt decrease from 1 to 2 clusters (the first bar in the graph) and then smaller changes in inertia as the number of clusters increases. This appears to be leveling off at 6 clusters (fifth dark bar on the figure). The right-hand side figure shows this 6 clusters solution in which the 1712 observations are classed in one of the six groups. Note that going from 6 clusters to 7 would not yield any major gain in maximizing between-cluster inertia. This is not sufficient criterion to decide on the number of clusters as our final solution. Two additional criteria for deciding on the number of clusters are the relative balance of cluster membership and the interpretability of the solution (Muthén & Muthén, 2000, Nylund et al., 2007, Nylund-Gibson and Choi, 2018, Shanahan et al., 2013, Stringaris et al., 2013, Weller et al., 2020). This is also demonstrated by van de Velden et al., 2019 using FAMD to illustrate its functionality.

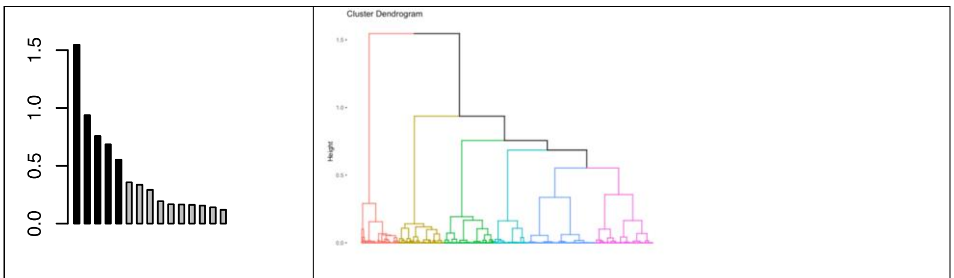

Figure 2.3.1 Inertia Gain by Increasing Number of Clusters and Dendrogram withSix Clusters Highlighted

The composition of these derived market segments can be presented in terms of the principal component scores and the original variables from Table 2.3.2 that are the vehicle characteristics each cluster fleet member wants to have for its next vehicle for the fleet. Table 2.3.2 shows all six market segments with membership that spans from 204 (~11.9% of the sample fleets) fleets to as many as 392 fleets (~22.9% of the sample fleets).

Table 2.3.2 Next Vehicle Market Segments and their Characteristics from Cluster Analysis

Characteristic	*SoonReplLargICE, N = 392*[1]	***LaterReplMedLargICE+**, N = 291*[1]	***SoonAddICE+**, N = 269*[1]
Purchase Or Lease			
Purchase New	214 / 392 (55%)	142 / 291 (49%)	125 / 269 (46%)
Purchase Used	178 / 392 (45%)	122 / 291 (42%)	102 / 269 (38%)
Lease	0 / 392 (0%)	27 / 291 (9.3%)	42 / 269 (16%)
Add Or Replace			
Add	0 / 392 (0%)	0 / 291 (0%)	269 / 269 (100%)
Replace	392 / 392 (100%)	291 / 291 (100%)	0 / 269 (0%)
Soon or Later			
Buying in <= 5yrs	392 / 392 (100%)	0 / 291 (0%)	231 / 269 (86%)
Buying in > 5yrs	0 / 392 (0%)	291 / 291 (100%)	38 / 269 (14%)
Fuel Type			
Electric or Hydrogen	0 / 392 (0%)	0 / 291 (0%)	1 / 269 (0.4%)
PHEV	16 / 392 (4.1%)	67 / 291 (23%)	76 / 269 (28%)
ICE (gasoline or other)	376 / 392 (96%)	224 / 291 (77%)	192 / 269 (71%)
Vehicle Size			
Small	112 / 392 (29%)	70 / 291 (24%)	107 / 269 (40%)
Medium	0 / 392 (0%)	92 / 291 (32%)	67 / 269 (25%)
Large	280 / 392 (71%)	129 / 291 (44%)	95 / 269 (35%)
Price	29,287.0 [30,000.0] (15,134.7)	27,332.7 [25,000.0] (15,014.5)	29,291.6 [30,000.0] (17,065.4)
MPGe	22.3 [20.0] (6.2)	26.7 [25.0] (11.1)	28.3 [25.0] (16.6)

[1] n / N (%); Mean [Median] (SD)

Table 2.3.2 Next Vehicle Market Segments and their Characteristics from Cluster Analysis (continued)

Characteristic	***SoonReplMedICE+**, N = 339*[1]	***SoonReplSmalPHEV**, N = 204*[1]	***ReplSmallEV+**, N = 217*[1]
Purchase Or Lease			
Purchase New	122 / 339 (36%)	70 / 204 (34%)	111 / 217 (51%)
Purchase Used	83 / 339 (24%)	53 / 204 (26%)	26 / 217 (12%)
Lease	134 / 339 (40%)	81 / 204 (40%)	80 / 217 (37%)
Add Or Replace			
Add	0 / 339 (0%)	0 / 204 (0%)	17 / 217 (7.8%)
Replace	339 / 339 (100%)	204 / 204 (100%)	200 / 217 (92%)
Soon or Later			
Buying in <= 5yrs	339 / 339 (100%)	187 / 204 (92%)	177 / 217 (82%)
Buying in > 5yrs	0 / 339 (0%)	17 / 204 (8.3%)	40 / 217 (18%)
Fuel Type			
Electric or Hydrogen	0 / 339 (0%)	0 / 204 (0%)	198 / 217 (91%)
PHEV	96 / 339 (28%)	204 / 204 (100%)	10 / 217 (4.6%)
ICE (gasoline or other)	243 / 339 (72%)	0 / 204 (0%)	9 / 217 (4.1%)
Vehicle Size			
Small	52 / 339 (15%)	203 / 204 (100%)	181 / 217 (83%)
Medium	272 / 339 (80%)	0 / 204 (0%)	26 / 217 (12%)
Large	15 / 339 (4.4%)	1 / 204 (0.5%)	10 / 217 (4.6%)
Price	32,892.6 [30,000.0] (18,699.0)	27,356.5 [30,000.0] (14,320.3)	46,832.3 [35,000.0] (42,482.7)
MPGe	26.8 [25.0] (11.5)	55.4 [45.0] (33.7)	99.6 [100.0] (50.8)

[1] n / N (%); Mean [Median] (SD)

The first segment is composed by 100% of fleets that plan to replace a current vehicle and not to add to their fleet. They also show a strong preference for large vehicles (71%) and 96% prefer ICE (gasoline or other). The median desired price in this segment is the same as the overall median (see also Table 2.2.1) but lower efficiency (MPGe). We name this market segment **SoonReplLargICE**. The second segment is also a group that just wants to replace a vehicle in their current fleet but after 5 years. This segment prefers medium and large vehicles powered by ICE but some of the respondents in this group also want to have PHEVs (23%). This segment aims at a median price lower than the overall median and efficiency higher than the overall median (this segment is named the **LaterReplMedLargICE+**). The third market segment is composed entirely of fleets that intend to add a vehicle with higher percentage preferring ICE but 28% prefer a PHEV. This segment's expected median price and efficiency are at the overall median levels. This segment is composed of fleets that at 86% plan to add this next vehicle within 5 years. We name this segment **SoonAddICE+.** All the fleets in the fourth segment intend their next vehicle to be a replacement of a current fleet vehicle and to procure this vehicle with 5 years. The majority of these fleets prefer medium size vehicles (80%) and divided between ICE (72%) and PHEV (28%). The preference of this segment for price and efficiency is similar to the previous one. We name this segment the **SoonReplMedICE+**. The last two segments represent the market segments that motivated our analysis here and they are as expected very different than the previous four.

The fifth segment is made exclusively of fleets that expect their next vehicle to be a PHEV and their strong majority to procure a small car to replace a current vehicle. Similarly, to all four previous segments they expectation is for a median price of $30,000 but a must higher efficiency (both the average and median are higher than the overall average and median MPGe). In addition, 92% of these fleets expect to procure their next vehicle within 5 years. We name this segment **SoonReplSamlPHEV**. The last market segment is heavily dominated by battery electric vehicles and/or hydrogen preferring fleets (91%) with the majority expecting to procure a small car (83%) and replace a current car (92%). This is the market segment that expects the highest price (mean of ~$46,000) and is by far the highest efficiency expecting segment (in essence fourfold the overall sample efficiency with median 100 MPGe). However, the fleets in this segment also show high intra-segment variability in the price expectation (see the standard deviation in Table 2.3.2 that is ~$42,500). We name this segment the **ReplSmallEV+.** All market segments, exception is the first segment, show a similar spread in their preference for purchasing new, used, or leasing a vehicle. Leasing appears to be very strong among the last three market segments hovering at around 40%. Also, the high percentage of fleets expecting to purchase used PHEV or BEV vehicles shows that the potential for a secondary market is very high for this type of vehicles and fleets but with many unknowns at this time. However, some early evidence suggests a few possibilities to increase information provision and reduce risk perception in secondary markets (Tal et al. 2021).

2.4 Market Segment Membership and Current Fleet Characteristics

As one should expect the respondents views about the next vehicle to add to the fleet are influenced by the fleet size and composition in terms of the types of vehicle fuels. We also expect the fleet location to influence preferences due to surrounding infrastructure availability. We also know from the literature photovoltaic and charging fleet owned equipment is correlated with the propensity to own and operate electric vehicles (Sugihara and Hardman, 2022, Sugihara et al., 2022). Table 2.4.1 is a Multinomial Logit model that uses as dependent variable the membership to one of the six market segments and as independent variables the fleet characteristics of Table 2.1.1. The reference category is SoonReplLargICE and all the coefficients should be interpreted accordingly. Preference of membership in any of the six market segments as a function of the size in terms of employees of the fleet owner company is not influenced by the size except for the group SoonReplSmalPHEV. The rest of the regression coefficients for this variable are not significantly different than zero meaning we have a uniform distribution of company sizes with each market segment.

When we consider the fleet composition and the number of vehicles by fuel type in the fleet, we see that fleets that already own and operate PHEVs and EVs are also more likely to seek as next vehicle a PHEV or EV. In contrast, fleets that own a higher number of ICE vehicle (Gasoline, Diesel, and CNG) are less likely to seek as next vehicle a PHEV or EV (see the negative coefficients corresponding to the group ReplSmallEV). As expected fleets in companies that made investments in charging with Volt240 chargers are more likely to select a PHEV or EV as next vehicle and also companies that have solar panels are more likely to select an EV vehicle as the next car in the fleet.

Construction companies are less likely to be in any of the groups shown in Table 2.4.1, which means they are more likely to seek large ICE vehicles as the next vehicle to procure (all coefficients in Table 2.4.1 are negative and many of them are significantly different than zero). Retail companies seem to only be unlikely to procure electric cars. Real estate, Professional, and Health companies are the ones with higher propensity for PHEVs and EVs. It should be noted that many professional companies are home-based consulting and service companies, and the preference of this group may coincide with residential preferences. Large urban areas (Los Angeles, San Francisco, and San Diego) that provide the infrastructure for charging and known to have shorter but more frequent trips are also more suitable for fleets that plan to procure PHEV and EVs. However, these three regions are also the regions with the highest representation in this sample with Los Angeles having 747 fleets (43.6%), San Francisco 415 fleets (24.2%) and San Diego 175 fleets (10.2%).

Table 2.4.1 Multinomial Logit Model Correlating Fleet Characteristics to Cluster Membership

	Dependent variable:				
	LaterRepl MedLargGas	Soon AddGas	Soon ReplMed	SoonRepl SmalPHEV	ReplSmall EV
Number of Workers	-0.0005	0.002	0.002	-0.013*	0.001
	(0.003)	(0.002)	(0.002)	(0.007)	(0.002)
Number of Gasoline Vehicles	-0.069**	0.010	0.003	-0.001	-0.245***
	(0.032)	(0.010)	(0.011)	(0.018)	(0.061)
Number of Diesel Vehicles	-0.186*	0.010	-0.152*	-0.492**	-0.342**
	(0.101)	(0.021)	(0.082)	(0.227)	(0.143)
Number of CNG Vehicles	-3.640***	-0.912	0.206	-1.488	-2.127**
	(0.009)	(0.694)	(0.265)	(0.947)	(0.967)
Number of PHEV Vehicles	-0.016	1.132***	0.125	1.728***	1.417***
	(0.463)	(0.336)	(0.396)	(0.330)	(0.337)
Number of Electric or Hydrogen Vehicles	-0.114	0.685*	0.265	0.598	1.534***
	(0.529)	(0.361)	(0.396)	(0.380)	(0.344)
Company has Solar Panels	0.227	-0.347	0.747*	0.603	0.931**
	(0.423)	(0.356)	(0.420)	(0.467)	(0.427)
Company has Volt240Chargers	-0.188	0.426	0.759	1.135**	1.466***
	(0.665)	(0.476)	(0.510)	(0.522)	(0.480)
Company has No Refueling	0.466	-0.287	0.914**	0.809*	0.551
	(0.380)	(0.316)	(0.394)	(0.468)	(0.441)
Company has Charging Equipment	-1.354	-0.981*	-1.199*	-0.192	0.365
	(0.868)	(0.532)	(0.613)	(0.498)	(0.462)
Note: *p<0.01 **p<0.05 ***p<0.01					

Table 2.4.1 Multinomial Logit Model Correlating Fleet Characteristics to Cluster Membership (continued)

	Dependent variable:				
	LaterRepl MedLargGas	Soon AddGas	Soon ReplMed	SoonRepl SmalPHEV	ReplSmall EV
Construction Company	-0.316	-0.238	-1.736***	-2.345***	-0.817**
	(0.242)	(0.239)	(0.372)	(0.613)	(0.415)
Retail Company	0.058	-0.058	0.224	-0.349	-0.808*
	(0.261)	(0.274)	(0.248)	(0.336)	(0.430)
Real Estate Company	0.187	-0.389	0.822***	0.197	0.990***
	(0.342)	(0.403)	(0.296)	(0.372)	(0.348)
Professional Company	0.424*	0.251	0.664***	0.803***	0.784***
	(0.224)	(0.237)	(0.213)	(0.236)	(0.256)
Health Company	0.888**	0.593	1.438***	0.801*	0.914**
	(0.401)	(0.424)	(0.368)	(0.442)	(0.460)
San Francisco Site	-0.213	0.212	0.361	1.095***	1.210***
	(0.221)	(0.239)	(0.230)	(0.342)	(0.342)
Los Angeles Site	-0.173	0.544***	0.696***	1.608***	0.994***
	(0.194)	(0.208)	(0.202)	(0.314)	(0.328)
San Diego Site	-0.193	0.168	0.165	1.311***	1.232***
	(0.291)	(0.316)	(0.302)	(0.396)	(0.400)
Constant	-0.410	-0.591*	-1.540***	-2.696***	-2.477***
	(0.393)	(0.331)	(0.407)	(0.528)	(0.512)
Akaike Inf. Crit.	5,491.445	5,491.445	5,491.445	5,491.445	5,491.445
Note: ***p<0.01 **p<0.05 ***p<0.01**					

2.5 Market Segment Membership and Fleet Managers Attitudes

In this section we expand the analysis to include attitudes expressed by the fleet managers' preference for the top attributes combined with attitudes. We study the correlation between the market segment membership with the top next vehicle characteristics in Table 2.1.2 (recall that table shows the frequency of the top 3 attributes according to the survey respondent of the fleet). Preliminary analysis showed that vehicle price has a negative correlation with EV as the next vehicle and MPGe has a positive correlation with PHEV and EV and they are as expected considering these two markets have high expectations/desires for efficiency and for the EV the expectation of the price is higher. So, managers who are sensitive to vehicle prices avoid EVs. Also, when the top attributes are cargo capacity (e.g., payload) and towing, the fleets are less likely to be in the last two segments that are also characterized by small vehicles and in 2016-17 when the survey was done there were not that many large electric vehicles with large payloads. This is also as expected considering the concerns of commercial fleet managers (Romjue, 2021, Brown, 2022). However, industry trends predict a major change in these attributes (KBB, 2023).

Another potential inhibition of considering PHEV and/or EV as the next vehicle to procure is when a company makes extensive use of outsourcing such as using rental cars, courier and delivery services, and taxi and TNC services. We did not find any correlation between courier and delivery services and membership in any one of the six segments here. However, we do find negative and significant correlation between renting vehicles with all five segments which means the more rentals a company uses the less likely it is to select a next vehicle of the type in each of the five segments. So, this may be a reflection of substitution between procuring a small and medium vehicle for any kind of fuel with rental services. In contrast, we find a positive correlation between frequency of taxi services and all five of the segments in Table 2.4.1. This indicates complementarity between the next vehicle and taxi/TNC services and not substitution and maybe the next vehicle is viewed as one that satisfies added demand that is not served by the current service provision offered by taxis and TNCs. However, a more detailed data analysis is required to identify the frequency and type of services for both potential substitution and complementarity (we return to this in another section of this report that considers specific fleet vehicles).

In this section we follow the analysis based on the flowchart of Figure 2.5.1.

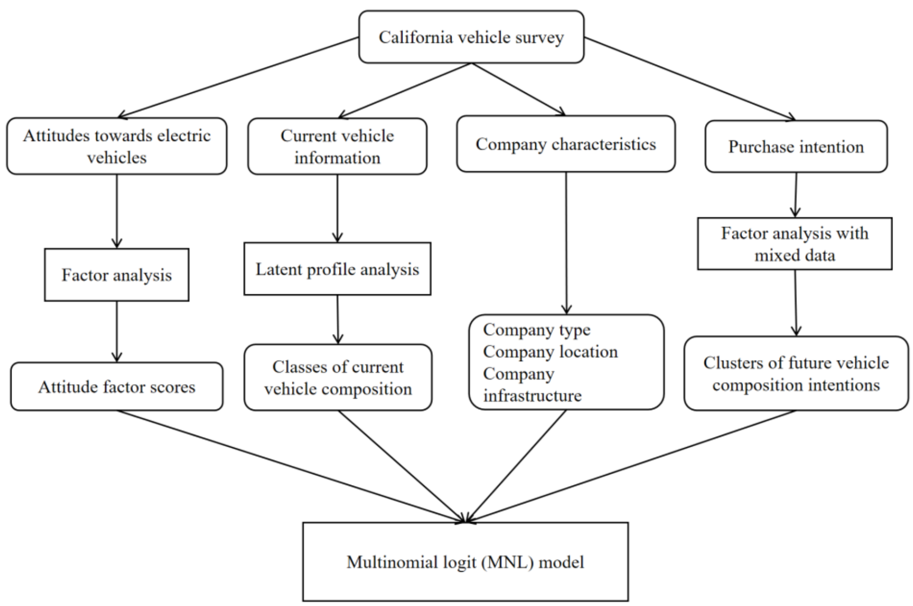

Figure 2.5.1 Workflow of exploring the impact factors of future market segments

2.5.1 Theoretical foundations

In general, there are several widely used theoretical foundations for purchase intention: (1) the theory of reasoned action (TRA) suggests that an individual's behavior is influenced by their *attitudes*, which refer to their positive or negative views of the behavior, and their *subjective norms*, which indicate the perceived social pressure from influential people to perform or not perform the behavior (Fishbein & Ajzen, 1975); (2) the theory of planned behavior (TPB) is an extension of TRA with an additional determinant (Ajzen, 1991; Yan et al., 2019), *perceived behavioral control*, which stands for the individual's perceived ability to perform the behavior; (3) the technology acceptance model (TAM) is another widely adopted model that proposes *perceived ease of use* and *perceived usefulness* as the fundamental elements of the adoption of information technology (Globisch et al., 2018; Venkatesh, 2000; Venkatesh & Davis, 2000); and (4) the unified theory of acceptance and use of technology (UTAUT) integrates the key components of multiple behavioral models and theorizes four direct determinants of behavioral intention: *performance expectancy*, *effort expectancy*, *social influence*, and *facilitating conditions* (Venkatesh et al., 2003). In more depth, *performance expectancy* is described as an individual's belief that using the object or system will assist them to make improvements in job performance. It is comprised of five elements from other models, including *perceived usefulness* from the TAM, *extrinsic motivation* from the motivational model (MM), *job-fit* from the model of personal computer utilization (MPCU), *relative advantage* from the innovation diffusion theory (IDT), and *outcome expectations* from the social cognitive theory (SCT). *Effort expectancy* is the degree of ease associated with using the system. Its concept is captured by three existing constructs: *perceived ease of use* (TAM), *complexity* (MPCU), and *ease of use* (IDT). *Social influence* is the extent to which a person perceives that significant others believe they should adopt the new system. As a direct determinant of behavioral intention, *social influence* can be illustrated as the *subjective norm* in TRA and TPB, *social factors* in MPCU, and the *image* in IDT. *Facilitating conditions* are defined as the extent to which a person evaluates that an organizational and technical infrastructure exists to support system use. This definition includes concepts from three distinct constructs: *perceived behavioral control* (TPB), *facilitating conditions* (MPCU), and *compatibility* (IDT). In 2004, Schulte et al. extended Peter and Tarpey's (1975) hypothesis that consumer purchasing behavior can be determined by *perceived risk* (a type of potential loss when consumers choose one product), *perceived return* (realistic benefits that consumers feel by adopting a product), and *expected net perceived return* by claiming that *perceived risk* and *perceived return* could be impacted by *past experiences* (possessing a car in particular), which also influences whether or not individuals adopt a product.

The aforementioned theories are founded on individual purchase intent. However, decisions in fleet are done by managers who may also be influenced by similar determinants in decisions making and we test this in the analysis of commercial fleets. In addition, according to existing studies, company background also plays an important role when managers decide whether or not to purchase vehicles and what type of vehicle to use, such as industry types and relevant infrastructures in companies (Golob et al., 1997; Zhang et al., 2019; Khan et al., 2021). Within this context, three main factors of purchase intentions can be proposed with regard to the available information provided by 2017 CVS: (1) attitudes towards behavior (TRA and TPB) (also associated with perceived returns and risks proposed by Schulte et al. (2004)), including both positive and negative attitudes toward BEVs and PHEVs described; (2) past experience from Li et al. (2017) and Schulte et al. (2004)'s models captured by current vehicle composition; and (3) company characteristics.

2.5.2 Factor analysis of attitudes

Despite the fact that both the TRA and the TAM imply that attitudes play a significant role in purchasing intentions and that the SCV provides pertinent attitude information, it is not a good idea to directly incorporate all these variables into the conceptual model, as doing so could result in a confusing cause-effect set of relationships. In this situation, factor analysis can be used to identify latent factors. In general, there are two forms of factor analysis: exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). In detail, the EFA is a tool for identifying the latent factors or dimensions that may be presented by a set of observed variables. It operates by analyzing the correlations between a set of observed variables, such as survey responses or scores assigned to answers to the survey questions, and then identifying the underlying factors that may be responsible for those correlations. An important output of EFA is a factor loading matrix (see Table 2.5.1), which depicts the strength and direction of the association between each observed variable and each factor. This matrix can be used to determine the most significant variables and factors, as well as to generate new hypotheses regarding the relationships between those variables. According to Tabachnick and Fidell (2001), a reasonable rule of thumb for the minimum loading of an item could be 0.32, which corresponds to about 10% overlapping variance with the other items in that factor. Cronbach's alpha is a commonly used parameter to assess the reliability of latent variables. It is commonly believed that the internal consistency is greater when it approaches 1 and that it is satisfactory when it exceeds 0.6. However, since this parameter assumes a unidimensional scale (Barbaranelli et al., 2014), it is inapplicable to the multidimensional attitude factors. In this case, the CFA model estimates can be used to evaluate latent factors. The CFA is commonly used after EFA, beginning with a model that specifies the relationship between observed variables and the underlying factors. The model generates parameters such as factor scores, which represent the strength and direction of the relationship between each observation and each latent factor. The CFA model can be evaluated using statistical techniques to determine how well it fits the observed data. Several statistical indices, such as Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI), Root Mean Square Error of Approximation (RMSEA), Root Mean Square Residual (RMR), Incremental Fit Index (IFI), Tucker–Lewis Index (TLI), Comparative Fit Index (CFI), and Normed Fit Index (NFI), can be employed to assess the model fitness. Table 2.5.2 provides a summary of the model fitness thresholds.

The factor loadings of the BEV and PHEV attitudinal variables for commercial fleets in 2017 are shown in Table 2.5.1. They suggest that there could be two latent factors for BEVs (one incentive/positive factor and one concern/negative factor) and three factors for PHEVs (one incentive/positive factor and two concern/negative factors). To be specific, the incentive factor of BEVs reflects reasons of choosing this type of vehicles, such as reducing environmental impacts, saving on fuel costs, carpool or High Occupancy Vehicle (HOV) lane access, and so forth, while the concern factor considers the limited driving range of BEVs, inadequate charging infrastructures, charging time, and stranded possibility. The positive factor of PHEVs considers fewer aspects than that of BEVs, but its negative factors include people's concerns about vehicle limitations in terms of seating capacity, hauling capacity, and vehicle styles, in addition to its high cost, uncertain battery, infrastructure issues, and long charging time. CFA in the Mplus software does not provide all of the aforementioned parameters, but these fit statistics are enough for evaluating model goodness. Mplus tends to provide one fit statistic from multiple families of fit statistics, as opposed to multiple fit statistics from a single family (Hu and Bentler, 1998). The RMSEA, TLI, and CFI of BEV and PHEV all pass the assessments.

Table 2.5.1 Factor loadings of attitudes toward BEVs and PHEVs

BEV variables	Loadings: Factor one	Loadings: Factor two	Label	PHEV variables	Loadings: Factor one	Loadings: Factor two	Loadings: Factor three	Label
Saving on fuel costs	0.971*			Carpool or HOV lane access	0.979*			
Reducing environmental impacts	0.995*			Reducing environmental impacts	0.934*			
Carpool or HOV lane access	0.938*			Convenience of charging	0.753*			PHEV_In
Convenience of charging	0.819*			Saving money overall	0.810*			
Vehicle performance	0.827*		BEV_In	Good lease terms	0.890*			
Good lease terms	0.842*			Limited seating capacity		0.528*		
New technology	0.746*			Limited hauling capacity		0.783*		PHEV_Con1
Politics of fossil fuels	0.871*			Limited vehicle styles		0.584*		
Saving money overall	0.835*			Too expensive			0.375*	
Vehicle styling, finish and comfort	0.771*			Battery life uncertainty			0.733*	
Limited driving range		0.799*		Cost of installing charging infrastructure			0.576*	PHEV_Con2
Lack of charging infrastructure		0.334*	BEV_Con	Lack of charging infrastructure			0.655*	
Time to charge the battery		0.495*		Time to charge the battery			0.755*	
Fear of getting stranded		0.446*						

Note: * indicates significant at 5% level; HOV represents High Occupancy Vehicle

Table 2.5.2 Estimates of the CFA

Fit indices	CMIN/DF	GFI	AGFI	RMSEA	RMR	IFI	TLI	CFI	NFI
Thresholds	<3.00	>0.90	>0.80	<0.10	<0.05	>0.90	>0.90	>0.90	>0.80
BEV	-	-	-	0.031	-	-	0.985	0.988	-
PHEV	-	-	-	0.026	-	-	0.978	0.982	-

2.5.3 Latent profile analysis of current market segments

The variables presented in Table 2.5.3 are used to categorize commercial fleets based on their current vehicle composition. According to these descriptive statistics, more than 90% of commercial fleets consist of fewer than or equal to five vehicles. In terms of vehicle fuel types, the majority of businesses continue to rely on internal combustion engines and small vehicles. In addition, they are more likely to purchase than lease new vehicles.

Table 2.5.3 Variables of current vehicle composition used in grouping fleets

Characteristic	N = 1,712[1]
Number of vehicles	
1	733/1,712 (42.82%)
2	428/1,712 (25.00%)
3	198/1,712 (11.57%)
4	112/1,712 (6.54%)
5	72/1,712 (4.21%)
6-10	97/1,712 (5.67%)
11-20	45/1,712 (2.63%)
20-50	15/1,712 (0.88%)
>50	12/1,712 (0.70%)
Proportion of vehicles (Fuel types)	
Electric or Hydrogen	0.1[0] (0.2)
PHEV	0.1[0](0.3)
ICE (gasoline or other)	0.8[1](0.3)
Proportion of vehicles (Body size)	
Car	0.4[0.3](0.4)
SUV	0.2[0](0.3)
Truck	0.3[0](0.4)
Van	0.1[0](0.3)
Proportion of vehicles (Purchase/Lease)	
Purchase new within last ten years	0.5[0.5](0.4)
Purchase used within last ten years	0.3[0.1](0.4)
Lease within last ten years	0.2[0](0.3)
[1] n / N (%); Mean [Median] (SD)	

On the basis of the observed variables in Table 2.5.3 and correlation analysis, the proportion of ICE vehicles and the proportion of vehicles purchased used within the last ten years are excluded from further analysis due to their high correlation (>0.6) with other variables (Chhablani et al., 2015). Then latent profile analysis (LPA), a type of finite mixture model, is utilized to identify latent subgroups of the current vehicle composition. The observed variables could be categorical, continuous, or both. The objective is to assign commercial fleets to latent classes such that the fit between observed data and estimated latent classes is maximized. Fit indices in Table 2.5.4 indicate that a six-profile solution is optimal (lowest AIC/BIC, high Entropy>0.9, and BLRT p-value 0.001). However, the solution involving five profiles is also acceptable. After comparing the proportion/number of the sample assigned to the smallest class (min_prop/min_n), we find that the six-class model has a class with less than 5% samples (56). In this case, the five-profile solution is selected due to the limited sample size of one class in the six-class model, as well as its interpretation and parsimony.

Table 2.5.4 Model fit statistics for latent profile analysis with one to six class

Fit statistics	1-Class	2-Class	3-Class	4-Class	5-Class	6-Class
Log-likelihood	-6531.908	-5117.454	-3893.293	-2728.995	-1568.675	-356.732
BIC	13242.506	10540.171	8218.420	6016.397	3822.328	1525.015
AIC	13111.816	10316.909	7902.586	5607.991	3321.349	931.464
min_prop	100.00%	6.02%	6.08%	3.27%	6.02%	3.27%
min_n	1712	103	104	56	103	56
max_prop	100.00%	93.98%	81.60%	62.21%	31.83%	47.26%
max_n	1712	1609	1397	1065	545	809
min_prob	1.000	1.000	0.988	0.968	0.965	0.961
p-value of BLRT	NA	0.000	0.000	0.000	0.000	0.000
Entropy	NA	1.000	0.995	0.956	0.960	0.971

Note: AIC, BIC: lower values of AIC/BIC indicate better model fit. min_prop/min_n: the proportion/number of the sample assigned to the smallest class. max_prop/max_n: the proportion/number of the sample assigned to the largest class. min_prob: minimum of the average probabilities for most likely class membership. BLRT: comparing the improvement between neighboring class models, a significant BLRT p-value indicates a significant improvement in model fit over the model with the prior number of classes. Entropy: measure the classification uncertainty with higher values indicating less uncertainty.

Figure 2.5.2 exhibits the means of eight continuous indicators (vehicle proportions) for each latent profile. As described in Table 2.5.3, the number of vehicles is a count but as recoded a categorical variable, thus it is not shown in this graph. Specifically, the first extracted group comprises 431 commercial fleets (25.18%). They typically utilize trucks with ICE that are not leased. This class is known as ***LPA1 (Gas_Truck_NoLease)***. The second profile is the largest of all (n=545; 31.83%) and has the lowest proportion of environmentally friendly vehicles. This group is more likely to have small and newly purchased vehicles. In this instance, it has the designation ***LPA2 (NoEle_Car_PurNew)***. The third group consists of 103 commercial fleets (6.02%) and displays a high proportion of electric or hydrogen-powered cars, as well as relatively high proportions of newly purchased and leased vehicles, indicating that they are the least likely to have purchased used vehicles. In addition, the number of vehicles statistics reveal that there are no fleets with more than three vehicles in this class. Consequently, we named this group ***LPA3 (Ele_Car_NoPurposeUsed_NoLargeCompany)***. The fourth profile contains 391 (22.84%) commercial fleets with a low proportion of clean or hybrid vehicles and a high proportion of new SUV purchases. Therefore, it has the label ***LPA4 (Gas_SUV_PurNew)***. The final category has 242 (14.14%) commercial fleets. Similar to LPA4, they typically utilize ICE-powered vehicles, but they are typically purchased vans. This last group is named ***LPA5 (Gas_Van_NoLease)***.

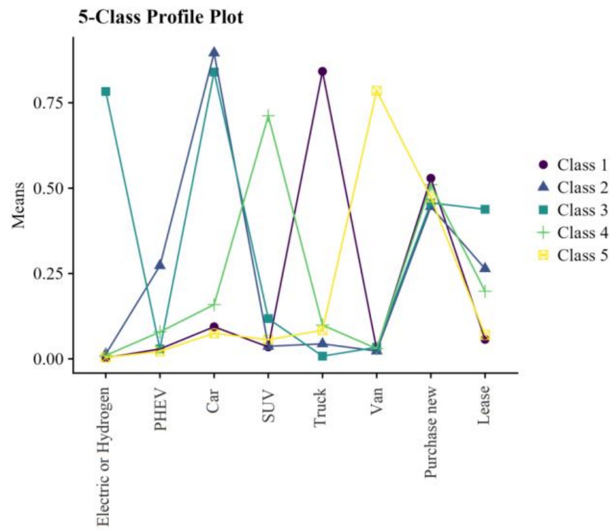

Figure 2.5.2 Means of continuous items in five-profile cluster solution

2.5.4 Additional variables as explanation of future market segment membership

The variables summarized in Table 2.5.5 represent company characteristics. It provides information on the frequency with which businesses utilize various services, such as rental vehicles (FreqRent), contract delivery services (FreqDelivery), and taxi services including Uber and Lyft (FreqTaxi). In addition, we take the industry classification into account, such as construction (CODE_Construction), real estate and rental and leasing (CODE_Estate), professional, scientific, and technical services (CODE_Profession), and health care and social assistance (CODE_Health). Furthermore, the profit motive and location of businesses are also considered. Lastly, whether or not the company has acquired charging equipment and/or upgrades in order to recharge vehicles is indicated by a dummy variable.

Table 2.5.5 Selected company characteristics

Variables	Statistics
FreqRent	**Using rental vehicles** Never: 759 (44.33%) Once or twice in the past 12 months: 573 (33.47%) 3 to 6 times in the past 12 months: 238 (13.90%) 7 to 11 times in the past 12 months: 90 (5.26%) 1 to 3 times a month: 38 (2.22%) 1 to 2 times a week: 9 (0.53%) 3 to 4 times a week: 3 (0.18%) Every day or nearly every day: 2 (0.12%)
FreqDelivery	**Using contract delivery service** Never: 1157 (67.58%) Once or twice in the past 12 months: 197 (11.51%) 3 to 6 times in the past 12 months: 96 (5.61%) 7 to 11 times in the past 12 months: 60 (3.50%) 1 to 3 times a month: 61 (3.56%) 1 to 2 times a week: 52 (3.04%) 3 to 4 times a week: 33 (1.93%) Every day or nearly every day: 56 (3.27%)
FreqTaxi	**Using taxi service** Never: 910 (53.15%) Once or twice in the past 12 months: 295 (17.23%) 3 to 6 times in the past 12 months: 230 (13.43%) 7 to 11 times in the past 12 months: 138 (8.06%) 1 to 3 times a month: 86 (5.02%) 1 to 2 times a week: 27 (1.58%) 3 to 4 times a week: 17 (0.99%) Every day or nearly every day: 9 (0.53%)
CODE_Construction	Yes: 163 (9.52%)
CODE_Estate	Yes: 133 (7.77%)
CODE_Prof	Yes: 378 (22.08%)
CODE_Health	Yes: 112 (6.54%)
ForProfit	Yes: 1,559 (91.06%)
Location	Los Angeles: 747 (43.63%) San Francisco: 415 (24.24%) San Diego: 175 (10.22%) Central Valley: 128 (7.48%) Sacremento: 82 (4.79%)
Charging equipment	Yes: 139 (8.12%)

2.5.5 MNL of future market segment

In order to provide additional insight into future market segments, an MNL regression model is employed to correlate next vehicle clusters with current vehicle composition, company characteristics, and managers' attitudes toward BEV and PHEV. ***SoonAddGas*** serves as the reference category. A Chi-Squared statistic of 1,096 (P-value less than 0.01) indicates that the model is a good fit for the data. Table 2.5.6 only includes coefficients that differ significantly from zero at the 0.1 level.

In terms of the current vehicle composition, ***LPA3 (Ele_Car_NoPurposeUsed_NoLargeCompany)*** was initially chosen as the reference group because we desire to concentrate on the transition of non-clean vehicles. However, the coefficients of ***LPA2 (NoEle_Car_PurNew)*** are not significantly different from those of LPA3, so LPA2 is removed from the model and becomes the reference group. This is due in part to the fact that LPA2 and LPA3 share certain characteristics, such as a preference for small, newly purchased vehicles. Since ***LPA4 (Gas_SUV_PurNew)*** is characterized by SUVs, fleets in this class are more likely to replace their current vehicles with medium-sized vehicles rather than small clean vehicles. Regarding ***LPA1 (Gas_Truck_NoLease)***, they are more likely to replace their vehicles with large gasoline-powered automobiles. All three profiles with vehicles of medium or large size are less likely to try electric/hybrid vehicles, primarily due to the high cost of large, clean vehicles.

With regard to company service use characteristics, it is noticeable that companies that frequently rent vehicles are less likely to replace their vehicles after five years, businesses that frequently use contract delivery services are less likely to purchase small gasoline or hybrid vehicles, and organizations that frequently use taxi services tend not to use large gasoline vehicles. Furthermore, the real estate and professional businesses are more likely to replace existing vehicles with small electric vehicles. In addition, for-profit organizations favor medium-sized vehicles (such as SUVs). Since Los Angeles is a developed urban metropolis, large gasoline automobiles are unpopular among local businesses. Moreover, companies that already have charging equipment for electric vehicles are less likely to adopt medium-sized vehicles in the near future. In addition, they are unwilling to buy medium- to large-sized gasoline vehicles when their current vehicles reach the end of their useful lives.

Attitudinal factors are the factor scores derived from CFA, which indicate the strength and direction of the association between each observation and each latent factor. As described in Section 2.5.2, there are two negative factors of PHEV (PHEV_Con1 and PHEV_Con2). However, since the coefficients of PHEV_Con1 are insignificant, they are excluded in this analysis. As expected, BEV_In is positively correlated with ***ReplSmalEV***, whereas PHEV_In is positively correlated with both ***ReplSmalEV*** and ***SoonReplSmalPHEV***. Managers of commercial fleets who are concerned about BEVs are also more likely to attempt gasoline-powered or plug-in hybrid electric vehicles (PHEVs), as PHEVs offer the option of using petroleum. In this case, the PHEV market has substantial promise, which could facilitate the future adoption of BEVs.

Table 2.5.6 Estimated parameters of MNL

Explanatory variables	**Dependent variable (Reference group: *SoonAddGas*)**				
	LaterReplMedLargGas	ReplSmallEV	SoonReplLargGas	SoonReplMed	SoonReplSmalPHEV
Current vehicle composition (Reference: LPA2 and LPA3)					
LPA4	0.163	-1.100***	-0.771***	0.706***	-1.389***
LPA1	0.273	-1.411***	0.513**	-0.807***	-1.978***
LPA5	0.119	-1.407***	-0.346	-0.03	-2.549***
Company characteristics					
FreqRent	-0.282***	-0.171	0.058	-0.044	-0.134
FreqDelivery	-0.082*	-0.091	-0.077*	0.012	-0.108*
FreqTaxi	-0.075	0.019	-0.128*	0.034	0.02
CODE_Construction	-0.174	-0.017	0.016	-1.298***	-1.389**
CODE_Estate	0.554	1.457***	0.508	0.920**	0.713
CODE_Profession	0.367	0.596**	-0.18	0.105	0.365
CODE_Health	0.398	0.515	-0.228	0.929***	0.205
ForProfit	0.19	0.318	0.153	0.746**	0.362
LosAngeles	-0.378**	-0.308	-0.294*	0.152	0.299
RefuelInstall	-1.877**	-0.095	0.172	-1.214**	-0.603
Attitudinal factors					
PHEV_In	-0.23	1.034***	-1.056***	-0.02	0.974***
PHEV_Con2	0.245	-0.849**	-0.372	0.172	0.027
BEV_In	0.311	1.677***	0.076	-0.002	0.316
BEV_Con	-0.108	0.304	0.522***	0.435***	0.565***
Constant	0.633	-0.268	0.650*	-0.643	0.308
Summary statistics Observations: 1,712 Log-Likelihood Restricted: -3022.6 (df=5) Log-Likelihood Unrestricted: -2474.6 (df=90) Chi-Squared test-statistic: 1096 ($p<0.01$***) McFadden R^2: 0.181					

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

3. Pinpointing Vehicle Replacement in Commercial Fleets

In this second portion of the commercial fleet analysis, we explore if there are specific commercial fleet vehicles that are more likely to be replaced by PEVs. We also explore if other services can function as substitutes of fleet vehicles such as transportation network companies (e.g., UBER, LYFT, DIDI) or parcel delivery services (e.g., FEDEX, UPS, DHL). In this analysis we use the data collected in 2019 (herein referred to as CEC2019) and we focus exclusively on the 5320 randomly selected vehicles from 2301 recruited commercial fleets.

3.1 Data Used to Pinpoint Vehicle Replacement

For each of the 5320 vehicles analyzed here survey participants were asked questions about the type of vehicle (fuel and body type), how the vehicle was used in the fleet, and if the vehicle is also used for personal reasons. The variables we use here to classify vehicles as potentially replaceable are answers to the questions:

1. *Could this vehicle be replaced by using ride-hailing services?* For 355 vehicles out of 5320 (7.6%) respondents answered they could be replaced by ride-hailing services.
2. *Could this vehicle be replaced by using delivery-hailing services?* For 252 vehicles out of 5320 (4.7%) respondents answered they could be replaced by delivery-hailing services.
3. *If this vehicle were replaced by an electric or hydrogen vehicle, what would be the minimum range (in miles) required for it to meet your business needs?* For 4916 vehicles out of 5320 vehicles, respondents answered the vehicles could be replaced by electric or hydrogen vehicles. The minimum range in miles was on average 227.7 miles (with median 200 miles).

These answers are not mutually exclusive, and we use cluster analysis to develop three distinguishable groups of vehicles and then study the correlation with vehicle characteristics as explained later. Table 3.1.1 shows the characteristics of each vehicle considered here. In subsequent analysis we will assess if there are systematic differences and commonalities in replacing specific categories of vehicles and the correlation with the type of replacement fleet managers expect to happen.

Table 3.1.1. Vehicle Characteristics

Characteristic	**N = 5,320**[1]
What is this vehicle primarily used for?	
Deliveries	1,330 / 5,320 (25%)
Transporting humans	1,370 / 5,320 (26%)
Sales	470 / 5,320 (8.8%)
Service	719 / 5,320 (14%)
Transporting Material	1,133 / 5,320 (21%)
Annual miles	18,497.0 [13,000.0]
Age of Vehicle	6.9 [5.0] (6.6)
Current Vehicle Efficiency (mpg)	24.3 [19.0] (20.3)
Can this vehicle be uses for personal use?	1,252 / 5,320 (24%)
What portion of the miles are for personal use?	5.5 [0.0] (12.3)
Vehicle purchased new	3,073 / 5,320 (58%)
Vehicle purchased new	1,450 / 5,320 (27%)
Vehicle is leased	697 / 5,320 (13%)

[1] n / N (%); Mean [Median] (SD)

Table 3.1.1. Vehicle Characteristics (continued)

Characteristic	N = 5,320[1]
Fuel the vehicle uses	
Gasoline	4,020 / 5,320 (76%)
Hybrid with gasoline	169 / 5,320 (3.2%)
Plug-in Hybrid Electric (PHEV)	600 / 5,320 (11%)
Diesel	204 / 5,320 (3.8%)
Fuel Cell Electric Vehicle (includes plugin)	177 / 5,320 (3.3%)
Gasoline - Ethanol flex fuel vehicle (E85 FFV)	119 / 5,320 (2.2%)
Vehicle Type	
Compact car	388 / 5,320 (7.3%)
Midsize car	444 / 5,320 (8.3%)
Large car	70 / 5,320 (1.3%)
Sports car	34 / 5,320 (0.6%)
Crossover car	402 / 5,320 (7.6%)
Medium crossover car	298 / 5,320 (5.6%)
Full suv	159 / 5,320 (3.0%)
Small van	388 / 5,320 (7.3%)
Large van	872 / 5,320 (16%)
Small pickup truck	340 / 5,320 (6.4%)
Full pickup truck	1,925 / 5,320 (36%)

[1] n / N (%); Mean [Median] (SD)

3.2 Cluster Derivation of Replaceable Vehicle

For each of the 5320 vehicles we used four variables that are the answers to the three questions about replacement by ride hailing passenger services, delivery-hailing services, electric vehicle, and desired range for the electric vehicle. Since these are not mutually and we would have too many combinations we use the same technique discussed in section 2.3. Figure 3.2.1 shows the three clusters derived using principal components analysis on three discrete variables (i.e., possible replacement by a PEV, possible replacement by ride hailing passenger services, and possible replacement by ride hailing delivery services, and a continuous variable that is the electric vehicle desired range). The three clusters (categories in the cluster membership variable thus developed) are below.

Category 1: Vehicles that can be replaced by PEV, or ride hailing passenger services (TNC), or ride hailing delivery services (PEV_Yes&TNC&Deliv). These are 383 vehicles (7.2% of the total).

Category 2: Vehicles that cannot be replaced by PEV but could be replaced by TNC or delivery services. These are 404 vehicles (7.59% of the total). This is labeled PEV_No&TNC&Deliv

Category 3: Vehicles that can be replaced by PEV but not by TNC or Delivery Services. We label these as PEV_Yes and they are 4533 vehicles (85.21% of the total).

To identify the composition of these three groups we develop a three-category multinomial Logit regression using as reference category the first category above. As membership variables we use the variables in Table 3.1.1. The estimation results are in Table 3.2.1.

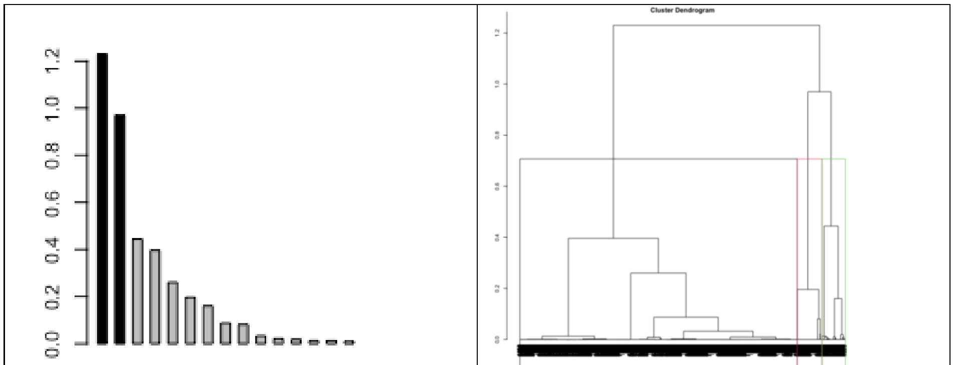

Figure 3.2.1 Inertia Gain by Increasing Number of Clusters and Dendrogram with Three Clusters Highlighted

Table 3.2.1 The Three Cluster Composition

Characteristic	PEV_Yes&TNC&Deliv, N = 383[1]	PEV_No&TNC&Deliv, N = 404[1]	PEV_ Only, N = 4,533[1]
Could this vehicle be replaced by an electric vehicle?			
0	0 / 383 (0%)	404 / 404 (100%)	0 / 4,533 (0%)
1	383 / 383 (100%)	0 / 404 (0%)	4,533 / 4,533 (100%)
Could this vehicle be replaced by using ride-hailing services?			
No	92 / 383 (24%)	340 / 404 (84%)	4,533 / 4,533 (100%)
Yes	291 / 383 (76%)	64 / 404 (16%)	0 / 4,533 (0%)
Could this vehicle be replaced by using delivery-hailing services?			
No	167 / 383 (44%)	368 / 404 (91%)	4,533 / 4,533 (100%)
Yes	216 / 383 (56%)	36 / 404 (8.9%)	0 / 4,533 (0%)
If this vehicle is replaced by an electric vehicle what would be the minimum range required?			
Range	223.3 [200.0] (213.8)	N/A (set to zero)	248.4 [200.0] (201.2)

[1] n / N (%); Mean [Median] (SD)

3.3 Multilevel Analysis of Cluster Membership

Each vehicle from among the 5320 vehicles in the database belongs to one of the 2301 recruited fleets to take part in this survey. These 5320 vehicles are a random selection from the fleet vehicles. However, this is not valid for fleets with 3 or less vehicles. In regression models that test the propensity of a specific vehicle to be replaced by a contract service or a PEV we need to account for the fleet in which the vehicle belongs and the different numbers of vehicles from different fleets. In this way we can account for any systematic answer to the vehicle-by-vehicle questions that is correlated with the fleet characteristics in which these vehicles belong. To do this a multilevel model is a good option and the equations below describe the regression model used here. Table 3.3.1 provides the model estimates. In this formulation the group Pev_Only is used as the reference so all the coefficients should be interpreted as relative to this reference and we get 2 regression coefficients (one for the group PEV_No&TNC&Deliv and another for the group PEV_Yes&TNC&Deliv).

The equations that define the multilevel model estimated here are:

Level 1 (vehicle): $\eta_{kij} = \ln(\frac{P(Y_{ij}=k}{P(Y_{ij}=K}) = \beta_{0jk} + \beta_{1jk}elevenplus_{ij} + \beta_{2jk}x_{2ij} + \cdots + \beta_{pjk}x_{pij}$

Level 2 (fleet):

$$\beta_{0jk} = \gamma_{00k} + \gamma_{01k}tinyfleet_j + \gamma_{02k}bigfleet_j + \gamma_{03k}Construction_j + u_{0jk}$$

$$\beta_{1jk} = \gamma_{10k} + \gamma_{11k}tinyfleet_j + \gamma_{12k}bigfleet_j + \gamma_{13k}Construction_j + u_{1jk}$$

$$\beta_{2jk} = \gamma_{20k}$$

$$\dots$$

$$\beta_{pjk} = \gamma_{p0k}$$

In these equations x are all the variables in the Table 3.3.1 model with the variables elevenplus, tinyfleet, and bigfleet highlighted in the equations because they play a special role.

In the Level 1 equation the first set of coefficients (β_{0jk}) are intercepts, slopes (β_{1jk}) for the variable elevenplus, and a set of other regression slopes (β_{2jk} to β_{pjk}). The index i = 1,…, 5320 for the vehicles, index j = 1,…, 2301 for the fleets, k= 2 for PEV_No&TNC&Deliv, k=3 for PEV_Yes&TNC&Deliv and K=1 for PEV_Only (the baseline/reference group). The index p=3,…, P is the other vehicles characteristics (x) that do not have a random slope.

In the Level 2 specification we have random intercepts that are a function of the two variables representing fleet characteristics (in essence size of the fleet divided into fleet of less or equal to 2 vehicles and fleets larger or equal to 50 vehicles) and they also have a random part (u). These random parts are also allowed to be correlated. This is the machinery that estimates the fixed effect vehicles characteristics on the probability of belonging to one of the three groups and the correlation with fleet characteristics that can "moderate" the impact of the xs on the propensity. We also get an estimate of the influence fleet size and type of business that owns the fleet (Construction in this case) play on this propensity to be in one of the three groups.

Table 3.3.1 Multilevel Multinomial Logit of Cluster Membership

	PEV_No&TNC&Deliv /PEV_Only	PEV_Yes&TNC&Deliv /PEV_only
(Intercept)	-2.700***	-3.281***
	(0.172)	(0.203)
Current use of this vehicle?		
Deliveries	-0.436*	1.089***
	(0.202)	(0.206)
Transporting humans	0.113	1.063***
	(0.169)	(0.207)
Sales	0.114	0.972***
	(0.205)	(0.245)
Transporting material	-1.198***	-0.282
	(0.294)	(0.274)
Vehicle is older than 10 years (elevenplus)	-1.230***	-0.351*
	(0.233)	(0.151)
Vehicle does less than 15 mpgs	-1.028***	-0.294
	(0.253)	(0.153)
Vehicle make/type		
Vehicle is large car	0.706	1.153***
	(0.435)	(0.328)
Vehicle is large van	-1.055**	0.101
	(0.338)	(0.169)
Vehicle is midsize car	2.285***	0.923***
	(0.154)	(0.185)
Vehicle is midsize crossover	0.009	0.491*
	(0.272)	(0.209)
Vehicle is small crossover	1.250***	0.729***
	(0.174)	(0.186)
Fleet has 2 or less vehicles (tinyfleet)	0.736***	0.090
	(0.129)	(0.124)
Fleet has 50 or more vehicles (bigfleet)	0.467	0.296
	(0.242)	(0.221)
Construction company fleet	-0.665**	-0.395*
	(0.203)	(0.168)
Variance Intercepts	0.289	0.313
	(0.001)	(0.002)
Variance of elevenplus coefs	0.131)	0.122
	(0.000)	(0.000)
Number of Fleets	2301	
Deviance	Null Model = 5031	This Model = 4449.2
Number of Vehicles	5320	

In Table 3.3.1 a positive and significant coefficient indicates a specific vehicle with the characteristic of the associated variable is more likely to be in the group represented by the column where the coefficient is than at the reference category (PEV_Only). For example, if the current vehicle in the fleets is transporting humans, is used for deliveries, or sales that vehicle is more likely to be in the group PEV_Yes&TNC&Deliv and not PEV_Only. In contrast, the coefficients for transporting humans and sales for the group PEV_No&TNC&Deliv are not significantly different than indicating that most likely this type of vehicle use is not fit for this group. It is important to identify which make/type of cars are more likely to be replaced by electric vehicles but also by contracted services. The midsize cars and small crossover cars are more likely to be in one of the groups in Table 3.3.1 instead of the PEV_Only group. Large cars are also more likely to be in the PEV_Yes&TNC&Deliv group. In contrast large vans are more likely to be in the PEV_Only group. The negative coefficients for the variable indicating how old a vehicle is (elevenplus) show that relatively younger cars (less or equal to 10 years) are more likely to be in the two groups of Table 3. However, these coefficients are also part of the random slope with positive covariance with the intercepts indicating the possibility of a more complex relationships within fleets (e.g., tradeoffs of using newer cars for some purposes as other cars age). Turning to the fleet size and type of firm that owns the fleet, we see that vehicles owned by a Construction business shows a negative propensity to be in the two Table 3.3.1 groups. However, the fleet size does not show this strong tendency. Note, however, this may be mitigated by allowing the random components to be correlated. This means there is something unobserved (i.e., not included in this model) that control membership in one of the groups. This type of model formulation allows one to also express these relationships in a probabilistic way using the odds ratios. These are in essence expressions of taking the exponential of the regression coefficients. Table 3.3.2 shows the odds ratios together with their estimation of lower and upper confidence intervals.

If a vehicle is used for transporting humans it increases its odds to be in the PEV_No&TNC&Deliv over PEV_Only by 12%. Similarly, if the vehicle is used for sales. However, if the vehicle is used for deliveries, transporting humans, or sales it increases its odds to be in the PEV_Yes&TNC&Deliv over PEV_Only by 197%, 189% and 164%. This makes perfect sense considering the two competing services even with PEVs are dedicated to deliveries and transporting humans. In contrast transporting material has odds ratios that are all lower than 1 and combined with the lower than 1 odds ratios for Construction fleets indicates that the baseline group is where most of this type of vehicle and fleets are . The type of cars that have higher probability of being in the PEV_No&TNC&Deliv group midsize and large cars plus crossover vehicles with some of them showing remarkably high odds ratios (9.829). We see a similar trend for the PEV_Yes&TNC&Deliv. The excluded cars from the models here are subcompact, compact and sports cars that are more likely to be in the PEV_Only group. Also absent here are pickup trucks that we know are cause for skepticism in commercial fleets [Evans, 2021, Kraft, 2023]. We did not find them to be a significant factor in group membership with this modeling approach.

Table 3.3.2 Odds Ratios and their 5% confidence intervals

	PEV_No&TNC&Deliv /PEV_Only			PEV_Yes&TNC&Deliv /PEV_Only		
	Odds Ratio	Lower Limit	Upper Limit	Odds Ratio	Lower Limit	Upper Limit
Intercept	0.067	0.048	0.094	0.038	0.025	0.056
Current use of this vehicle?						
Deliveries	0.647	0.435	0.962	**2.970**	1.982	4.450
Transporting humans	**1.120**	0.803	1.561	**2.894**	1.929	4.341
Sales	**1.121**	0.750	1.676	**2.643**	1.634	4.276
Transporting material	0.302	0.170	0.537	0.754	0.441	1.291
2~elevenplus	0.292	0.185	0.462	0.704	0.523	0.946
2~badmpg	0.358	0.218	0.587	0.745	0.553	1.005
2~large	**2.025**	0.863	4.755	**3.168**	1.665	6.029
2~lvan	0.348	0.180	0.675	1.106	0.795	1.540
2~midsize	**9.829**	7.273	13.284	**2.516**	1.750	3.618
2~mcrossover	1.009	0.593	1.719	**1.634**	1.084	2.462
2~crossover	**3.490**	2.481	4.908	**2.072**	1.440	2.982
2~fleet2car	**2.088**	1.621	2.689	1.094	0.859	1.393
2~largefleet	**1.596**	0.994	2.563	**1.345**	0.873	2.072
2~Construction	0.514	0.345	0.766	0.673	0.485	0.936

Interestingly, vehicles in very small fleets (one or two cars) have much higher odds of being in a group that does not see replacing their cars with PEVs. In addition, cars from relatively large fleets (with more than 50 vehicles) are also showing higher odds to be in the PEV_No&TNC&Deliv (59.6% higher) and in the PEV_Yes&TNC&Deliv (34.5% higher) than in the PEV_only. However, the confidence intervals of the large fleets include the value of 1 (in essence equal chance with PEV_Only) and the findings should be interpreted with caution. In other words, fleets that are larger than two vehicles are more likely to replace current vehicles with PEVs but not substitute them with TNC or contract deliveries.

3.3 Summary and Conclusions Pinpointing Vehicle Replacement

The analysis in this section uses data collected on 5320 randomly selected vehicles from 2301 recruited commercial fleets for which specific questions about substitution were asked by pinpointing vehicles considered in each fleet. We first develop groups of vehicles that have similar replacement propensity using cluster analysis on mixed data to classify vehicles in groups of no replacement by electric cars, replacement by a combination of electric cars and contract services, and replacement by electric cars but not contract services. Then we analyze the vehicles that will be replaced to identify characteristics making them suitable for each of the three types of replacement. The analysis here shows first that the majority of fleet vehicles can be replaced by electric vehicles. We also find diversity in vehicle replacement propensity that is a function of vehicle age, size, and type of utilization of the vehicle to be replaced. We also find differences based on fleet size and the type of business of the owner firm of the fleet.

This analysis shows that contract and ride hailing services can be a major competitor of ICE vehicles in fleets. This aspect has been neglected in the EV literature and in this paper we show both competition with PHEV and BEVs but also complementarity. The questions here that included vehicle fuel, type/size, but also current use and the possibility of replacement of these current fleet vehicles and their substitution by other types of vehicles as well as contract services enables this type of analysis providing evidence of the continuum of complementarity of uses as portfolios of services but also replacement of older vehicles and less efficient vehicles. Contract services can function as substitutes of fleet vehicle purchase and may be viewed as services provided by transportation fleets to other industries. One limitation, however, is the absence of a substantial sample clearly identified as TNCs such as Uber, Lyft and total absence of couriers and express delivery services. In fact, TNCs are classified under "Transportation and Warehousing" with a small percentage in this sample and fleets of couriers and express delivery services (UPS, FedEx, DHL, etc) are entirely absent. This should be rectified in future surveys to explore the impact of recent trends among these services in favor of electric vehicles in basic and premium services (UBER, 2023) and the ongoing electrification of delivery service companies (UPS, 2022). In any case, however, the findings here support a different type of public incentive than tax rebates. For example, governments could provide vouchers for the use of EV ride hailing and scrappage programs targeting specific vehicles in fleets with options to engage service contracts with delivery services that also use EVs.

4. Analysis of Hypothetical Choice Scenarios

4.1 Data

In this section we analyze the CVS commercial stated preference (SP) questionnaire data (hypothetical choice scenario data). The primary objective of this type of data collection is to identify the items necessary for estimating utility functions and to establish discrete choice (and related) models. The project team collecting the data emphasized the importance of establishing a set of fundamental values around which attributes would be varied in accordance with an experimental design. In the SP survey, each commercial fleet manager was subjected to eight experiments, each with four alternatives. This means that managers chose one of four options in a repeated choice process eight times based on various combinations. In this survey (2017), the characteristics that varied among the options are vehicle type, vehicle make/model, model year, vehicle price, MPGe, vehicle range, etc. The 2019 CVS also collected similar information.

4.2 Discrete choice model

When attempting to explain or estimate a decision involving two or more discrete options, it is common to employ discrete choice models (DCM). The objective of the 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 limited options available. 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. The greater the utility value of an alternative, the more the decision-maker prefers it. In general, its formula is as follows:

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

Field Code Changed

Specifically, the utility (U_{ij}) of a person i is a function of individual 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 a DCM, willingness to pay (WTP) is an essential part 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.

4.3 Comparison between 2017 and 2019 vehicle choices

Two basic models are developed based on 2017 and 2019 CVS surveys to investigate changes in vehicle preferences over time. The following vehicle attributes are included in the basic models: (1) vehicle range (miles per gallon equivalent); (2) annual maintenance cost ($); (3) miles per gallon equivalent; (4) acceleration to 60 mph (seconds); (5) model year (here, the age of the vehicle is calculated by using 2017 minus the model year); and (6) vehicle price ($). Since the 2019 CVS collects vehicle model year in a different way, thus the vehicle age cannot be estimated.

Table 4.1.1 provides a summary of the coefficients of our basic discrete choice model and the Chi-square suggests our basic model performs better than the null model (no explanatory variables). In 2017, both vehicle range and vehicle efficiency (MPG) are positively correlated with the preference of commercial fleet managers. This makes sense, as the better the vehicle's performance, the more likely companies are to select it. While the vehicle with higher annual maintenance costs, slower acceleration, a greater age, and a higher price is less likely to be chosen. In contrast, 2019's results are not all that reasonable. The negative MPG coefficient suggests that as vehicle efficiency increases and acceleration time decreases, managers are less likely to choose the vehicle. This is contrary to our common sense and may be the result of data acquisition issues (e.g., respondents failed to fully understand the question and/or the experimental design was not executed as planned).

Table 4.1.2 suggests that companies are willing to spend approximately $58 more to increase vehicle range by one mile, $17.412 more to decrease annual maintenance costs by one dollar, roughly $294 more to increase MPG by one mile, $1,881 more to reduce acceleration time by one second, and $2,811 more to acquire a vehicle that is one year newer in 2017. However, as stated previously, the 2019 estimates are unrealistic. For instance, it implies that managers would like to pay an additional $21771 to increase the acceleration time by one second, which is nonsensical. The 2019 dataset is therefore excluded from our subsequent analysis.

Table 4.1.1 Parameter estimates of basic vehicle choice models in 2017 and 2019

Variables	2017		2019	
	Coefficients ($\times 10^{-3}$)	Z-Value	Coefficients ($\times 10^{-3}$)	Z-Value
Vehicle range	1.321	27.082***	2.468	25.523***
Maintenance cost	-0.400	-4.257***	-0.500	-24.914***
MPG	6.744	13.279***	-1.638	-3.792***
Acceleration	-43.184	-9.648***	64.194	11.452***
Vehicle age	-64.548	-8.000***	-	-
Vehicle price	-0.023	-26.808***	-0.003	-5.609***
Summary statistics				
Log-likelihood of the null model	-14,129		-19,363	
Log-likelihood of the basic model	-18,051		-24,621	
Chi-square	7,843.8***		10,514***	

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

Table 4.1.2 Willingness to pay in 2017 and 2019 (respect to vehicle price)

Variables	2017		2019	
	Coefficients	t-Value	Coefficients	t-Value
Vehicle range	-57.539	-18.586***	-836.842	-5.371***
Maintenance cost	17.412	4.135***	169.724	5.402***
MPG	-293.726	-13.078***	555.571	2.930***
Acceleration	1,880.734	9.478***	-21,771.355	-4.812***
Vehicle age	2,811.167	8.959***	-	-

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

4.4 Findings from 2017 commercial fleets

The commercial survey recruiting effort for the pretest did not yield enough completed surveys to achieve the sample size requirement (2,000). In this case, the project team collaborated with the manager of the Commission agreement to distribute more postcards and come up with updated administration strategies. To be more specific, in February of 2017, they collaborated with InfoGroup, a marketing services provider, to randomly email a statewide sample of California businesses (n=80,000). In order to collect the remaining portion of the sample size that was not collected through the postcard administration or the InfoGroup email outreach, they worked with Research Now, an online market research panel provider, to undertake a targeted email outreach to California firms. Plus, the project team also included additional commercial fleets that use PEVs (12.27% of total samples) because their initial sample size was too small. In this context, final samples were not completely collected at random. For an unbiased estimate, we also discuss the results with only random samples (excluding PEV postcards) in this section.

Despite the fact that the coefficient of MPG is insignificant for random samples, the coefficients of other variables are similar to the results based on all records (Table 4.4.1). In terms of the WTP, Table 4.4.2 indicates that the estimates of all records underestimate how much money people would be willing to pay more to increase vehicle range and decrease vehicle age and overestimate the number of money people is willing to pay more to decrease annual maintenance costs and decrease acceleration time. specifically, compared to the WTP of all samples, managers would prefer to pay roughly $300 less to decrease the acceleration time from zero to 60 mph by one second. However, they are prepared to pay $117 more for a vehicle that is one year newer than the findings obtained from the entire sample dataset.

Table 4.4.1 Parameter estimates of basic vehicle choice models in 2017 (excluding PEV postcards)

Variables	2017	
	Coefficients ($\times 10^{-3}$)	Z-Value
Vehicle range	1.467	26.861***
Maintenance cost	-0.332	-3.388***
Acceleration	-39.560	-8.283***
Vehicle age	-73.594	-8.701***
Vehicle price	-0.025	-27.033***
Summary statistics		
Log-likelihood of the null model	-12,291	
Log-likelihood of the basic model	-15,742	
Chi-square	6,902.2	

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

Table 4.4.2 Willingness to pay in 2017 (excluding PEV postcards)

Variables	2017	
	Coefficients	t-Value
Vehicle range	-58.373	-18.931***
Maintenance cost	13.209	3.332***
Acceleration	1,573.937	8.230***
Vehicle age	2,928.009	9.898***

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

In order to better understand the decision-making process, we include random parameters in the DCMs. They presume that the coefficients of those variables follow a normal distribution and are not fixed. However, Table 4.4.3 demonstrates that the explanatory variables have no random impact on vehicle selection. This is confirmed by the insignificance of the coefficients of standard deviations for selected variables and Chi-square. It suggests that more complicated models are not always superior and that our previous basic models are enough for analysis and computation of WTP.

Table 4.4.3 Parameter estimates of vehicle choice models with random parameters in 2017

Variables	All records		Excluding PEV postcards	
	Coefficients ($\times 10^{-3}$)	Z-Value	Coefficients ($\times 10^{-3}$)	Z-Value
Vehicle range	1.321	27.081***	1.471	26.936***
Maintenance cost	-0.400	-4.257***	-0.326	-3.324***
MPG	6.744	13.278***	-	-
Acceleration	-43.183	-9.648***	-39.446	-8.259***
Vehicle age	-64.548	-7.997***	-73.150	-8.649***
Vehicle price	-0.023	-26.808***	-0.025	-27.005***
sd. Vehicle range	0.001	0.007	0.002	0.011
sd. Maintenance cost	0.005	0.018	0.035	0.133
sd. MPG	0.087	0.038	-	-
sd. Acceleration	0.694	0.035	1.610	0.081
sd. Vehicle age	0.511	0.031	0.187	0.011
Summary statistics				
Log-likelihood of the basic model	-18,051		-15,742	
Log-likelihood of the basic model	-18,051		-15,742	
Chi-square	0.004		0.026	

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

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Data Management Plan

Basic Information

Principal Investigator: Konstadinos G. Goulias
Other Participants in Research Activities: Hui Shi (PhD student 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. Analyses of electric vehicle demand by commercial fleets in the California Energy Commission vehicle surveys of 2017 and 2019.
2. The data are available widely at the NREL website (www.NREL.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.